Factor Income Dynamics: An Exploration

Freeman, Daan

DOI:
10.33612/diss.125326165

Publication date:
2020

Factor Income Dynamics: An Exploration

Daan Freeman

Publisher: University of Groningen
Groningen, The Netherlands
Printer: Ipskamp Printing
Enschede, The Netherlands

ISBN: 978-94-034-2669-3
eISBN: 978-94-034-2668-6

Factor Income Dynamics: An Exploration

PhD thesis

to obtain the degree of PhD at the
University of Groningen
on the authority of the
Rector Magnificus Prof. C. Wijmenga
and in accordance with
the decision by the College of Deans.

This thesis will be defended in public on

Monday 25 May 2020 at 11.00 hours

by

Daan Freeman

born on 21 May 1991
in Groningen

Supervisors
Prof. M.P. Timmer
Prof. R.C. Inklaar

Assessment Committee
Prof. H.H. van Ark
Prof. M. O'Mahony
Prof. A.M. Salomons

Acknowledgements

This dissertation would not have been possible without the help of my two supervisors Robert Inklaar and Marcel Timmer, to whom I'm grateful for their invaluable support. Robert, thank you for tolerating me through two master theses, one research assistantship, and one doctoral dissertation. Doing research with you for the past five years or so has been a pleasure and has fostered my interest in research. Marcel, I would also like to thank you for all your support and feedback during the course of my dissertation. I'm glad you decided to move with me to the CPB, and look forward to continuing our collaboration.

I would express my appreciation for the reading committee for reviewing and evaluating my thesis, Bart van Ark, Mary O'Mahoney, and Anna Salomons. In addition, my gratitude towards the corona (the committee, not the virus) for being so flexible as to agreeing on proceeding with my defense online, and in such trying times. Throughout the course of my PhD, I also had many friends and colleagues without whose support, this PhD dissertation would not have been possible (or maybe it would have been better, without all your distractions). Stefan, you have been my friend since our double-degree masters and then you became my officemate during our PhDs. Thanks for all the laughs, the help, and the good times. Johannes, I tip my hat to you for all the jokes and for the plant, which I'm hoping has survived its corona-quarantine.

Maite, we go way back. Without your talents at organizing PhD trips and activities, our PhD trajectory would have been much less fun. Juliette, thanks for all the times squashing. Though I did find another squash-buddy in the Hague, I still think you're one of the most empathetic people I've met. David, thanks for being the funny guy that you are and all the coffee breaks. Joeri, though you ditched our game of thrones sessions to take ballroom dancing lessons, I still like you. Thanks for being a great officemate and for putting up with me all this time. Christian, I miss our Sunday brunches and our philosophical discussions. Thanks for adding sophisticated accents to my weekends.

I would also like to thank Aobo, Ibrahim, Ferdinand, Romina, Wen, Timon, Fred, Nikos, Eda, Marianna, and all the other GEM people, for being excellent colleagues. One does not simply complete a PhD without VrijMiBos, so cheers to Duc, Jos, Nick, Daniel, Mart, and Tobi for all the beers. A special shout-out to those with whom I shared a peculiar office (the Fish Bowl): Nikki, Bingqian, Adriana, and also all the other 9th floor people who were there at the start of the PhD-journey.

A salute to those who persevered with me during our tough ReMa days: Annelies, Guus, Sargis, Nazik, Eva, Manon, and Ruben. I would also like to thank all the others who have been there at some point along the way: Bert, Frank, Miralda, and Lennart.

As part of my PhD, I spent five months at the CPB. This great and educational time would not have been possible without my supervisors. Gerdien, Harro, Leon and others, thanks a lot for welcoming me and I look forward to continuing our work together.

Finally, I would to thank Elissa who, with love and support has helped me immensely, especially in the final months of my PhD. Jim and Anne, thanks for all the video-, tabletop-, and boardgames. You guys are the best. Last but not least, I would like to thank my mom and dad for their unconditional support during my PhD despite my poor attempts at explaining what I actually spent the last three years doing. I love you.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Inequality in terms of income and wealth has recently received growing attention inside academia and has been at the forefront of societal debates in the developed world and beyond. Particularly with the work of Piketty (2015), concerns have arisen about the inequality impact of widespread changes in the factor income distribution. These concerns are fuelled by the declining income share of labour, which is generally much more equally distributed among people than income derived from capital assets (Milanovic, 2016). Because of this, changing factor income shares can reduce the equality of the overall income distribution between people (Kuznets, 1955).

It is important to know how income shares are shifting and what drives these developments to evaluate the inequality consequences, among other things. The literature has found that the labour income share has declined, but at the same time there is little indication that the income share of tangible capital has experienced an offsetting increase, leaving a gap of unexplained income. Given this gap in the factor income distribution, an important question remains; which factors are gaining, or rather, where is the money going?

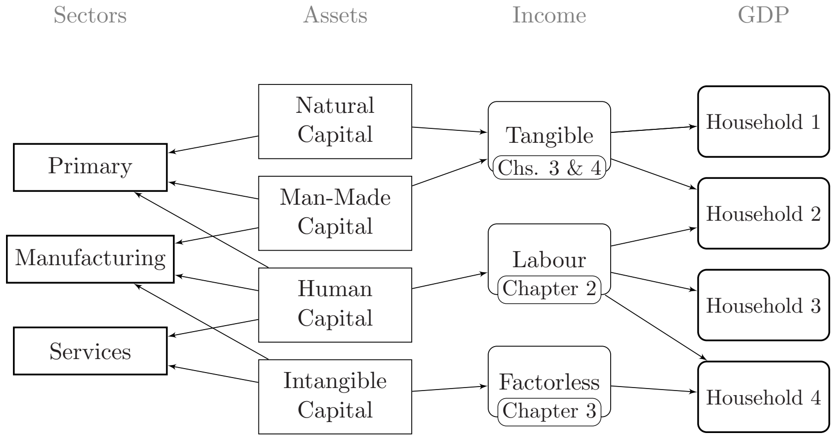
The shift in the factor income distribution away from labour and tangible capital also reflects more fundamental changes in the economy. New technologies and developments like globalisation have changed how and where production factors are used, altering the factor income distribution (Acemoglu and Restrepo, 2016). Studying the changing factor income shares is therefore important for understanding how these developments affect the economy.

My dissertation weighs in on these matters by exploring how the returns to production factors change over time and differ across places. In doing so, its overarching contribution is the notion that the developments and impacts of using different production factors are highly dependent on context, like the location and the level (i.e. firm/time/country) under consideration. In this introductory chapter, I will use the Netherlands as an example to illustrate this point. More specific discussion, analyses and results are presented in the subsequent chapters.

1.1 Background

To frame the discussion, it is helpful to examine the structure of Gross Domestic Product (GDP), or total income, in terms of its contributing factors of production. Consider a very simple representation of the economy, where firms produce goods and services by employing labour and using capital inputs, both supplied by households. The firms then sell their goods and services to generate revenues, which they use to compensate the households for the labour and capital inputs. The households thus receive income, in the form of wages and compensation for the use of the capital inputs. In this simple example, the distribution of income between labour and capital is the factor income distribution.

Figure 1.1: Gross Domestic Product (GDP) and Underlying Factors of Production



Moving on from this example, figure 1.1 outlines the structure of the factor income distribution in more detail. Leftmost, I distinguish between the three main sectors of the economy. The figure shows four types of factor inputs, or productive assets. Natural capital and man-made capital, human capital which is the stock of labour, and intangible capital (more discussion below). Arrows from the sectors to the assets indicate which assets firms in each sector tend to use most intensively in their production.

When used in production, each of the assets generates income flows for their owners, the households. Rather than only distinguishing between labour and capital income, the figure identifies three income flows: *labour*, *tangible* capital, and *factorless* incomes. Labour income consists of the rewards for the labour services provided by households. The arrows in the figure show nearly all households receive some labour income, indicating it is distributed relatively equitably across households. This also means that a decline in the labour income share could have a profound impact on inequality, in line with Piketty (2015). Chapter two explores the developments of the labour share in more detail.

Figure 1.1 also shows the tangible capital income flow, the rewards for the owners of physical capital assets. This income is derived from the use of tangible assets like machines, computers, buildings. These are man-made, physical assets and used by almost every firm to produce goods or services. Chapter three provides more details on the income share of man-made tangible capital. Similarly, natural capital assets are also tangible assets and are assets endowed by nature, like land, forests, and sub-soil assets. Chapter four focusses on these assets in a cross-country productivity comparison. The income generated by tangible capital income is less equally distributed than labour income, i.e. fewer households receive income from (indirectly) owning tangible capital assets than from their labour (Milanovic, 2016).

The third income flow in figure 1.1, factorless income, is less straightforward. Research has found that when labour and tangible capital income are accounted for, a part of GDP remains (Karabarbounis and Neiman, 2018; Barkai, 2016). At least a part of this factorless income consists of income generated by the use of intangible assets. These assets do not necessarily have a physical presence in the world, yet are often also vital for production. Examples of intangible assets are software, R&D, and brand names (Corrado et al., 2017; Haskel and Westlake, 2017).

The study of intangibles is relatively new and their measurement is still widely debated in the literature. The difficulty of incorporating intangible assets in this framework stems from the characteristics that set the intangible assets apart from their tangible counterparts. Particularly, the scalability of intangibles allows them to be used at the same time in different locations (Haskel and Westlake, 2017). Especially if located and used across borders, measurement of intangible income is very difficult. Chapter three conducts a more in-depth exploration of the income derived from intangible assets.

Using current data and standard capital income assumptions a residual part of factorless income remains unaccounted for, even when income derived from intangible assets is taken into account. The composition of this residual remains mostly unknown. Doraszelski and Jaumandreu (2013) establish that returns on knowledge intangibles are likely much higher than those on physical assets due to a sizeable compensation for the uncertainty of intangibles. Therefore, the residual may be the result of measurement error or incorrect assumptions regarding income flows from intangibles[1].

All these difficulties suggest that even if all assets are measured correctly, it might still be difficult to account for income fully. In chapter three, I explore this issue and find that some of the residual income can be assigned to capital income, and some to intangible income, depending on how they are quantified. However, to be able to account for all income, more research is required. Similarly, little is known about the distributional effects of a shift towards intangible assets and factorless income. However, intangible assets are likely concentrated among a relatively limited group of larger firms capable of funding significant intangible investments (Haskel and Westlake, 2017). The associated income flows are probably similarly concentrated, suggesting that rising factorless income might increase income inequality.

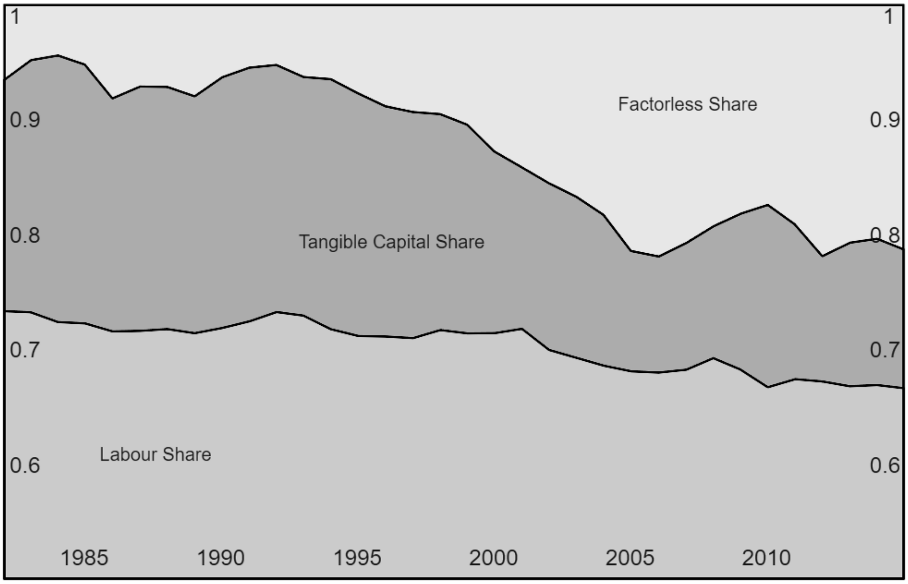
Figure 1.2 illustrates there has indeed been a significant shift towards factorless income. The figure shows the developments of the average factor income distribution since the early 1980s across 10 OECD economies (the 50% not shown is entirely labour income). It shows that the labour share has been on a steady decline throughout the entire period. At the same time, the income share of tangible capital seems to have declined even more significantly. Both declines are mirrored by a rising share of factorless income, its increase has been especially rapid during the 1990s and early 2000s. The development of the factorless share is particularly important in the Netherlands, where it rose over 5 percentage points since the early 2000s, exclusively at the expense of the tangible income share.

1.2 State of the Literature

For a long time, the focus of neoclassical economics has been on the income shares of labour and tangible capital, often assuming them constant and exhaustive of all income (Milanovic, 2016). However, this was the case for good reason, as the developments of the factor income

[1] Other potential causes of mismeasurement are the treatment of taxes, the allocation of income generated by the self-employed, own-accounted invest (in intangibles), and depreciation of assets. All of these have proven difficult to measure and require assumptions that might introduce error.

Figure 1.2: Distribution of the Income Shares of Labour, Tangible Capital, and Other Income



Note: Values are weighted averages of 10 OECD countries and the tangible capital share is based on estimates using a long-term 'safe' rate of return; see chapter 3 for details.

distribution were stable until the early 1980s. Similarly, at that time the shares of tangible capital and labour accounted for virtually all of GDP (Jones, 2016).

The constancy of the factor income distribution was already remarked on by Keynes (1939), who called it "a bit of a miracle", as he found no good reason why it should remain stable. Despite this remark, Kaldor (1957) immortalised the stability of the factor shares as "remarkable historical consistency". More recently, this stability has been breaking down as found and discussed by many others who documented a declining labour share[2]. Piketty and Zucman (2014) propelled the study of factor shares into the mainstream by linking it explicitly to wealth and income inequality. Not much later, Barkai (2016) and Karabarbounis and Neiman (2018) also documented declines of the tangible capital share.

With this renewed attention for the factor income distribution, the discussion in the academic community has proceeded on two fronts. Notably, the measurement, and the drivers of factor income share changes. First, the measurement side of the literature aims to establish with the greatest possible accuracy, the developments of the factor income distribution. Several key measurement issues are identified. One of the issues is the income generated by self-employed persons, which is hard to assign to particular factors due to the lack of an explicit wage-bill for the self-employed (Gollin, 2002; Elsby et al., 2013). Furthermore, the literature in this debate has largely focussed on the United States, largely ignoring the issue in other countries, or across countries in internationalised production processes (Elsby et al., 2013; Autor et al., 2019; Hsieh and Rossi-Hansberg, 2019).

Karabarbounis and Neiman (2018), Autor and Salomons (2018) and Dao et al. (2017) present evidence that labour shares are on the decline in many countries across the world. However, Döttling et al. (2017) and Cette et al. (2019) show labour share declines are much more limited outside of manufacturing in most countries or absent altogether in others. For example, in the Netherlands, the labour share decline has been less severe than in some other countries, and mostly absent since 2000. Chapter 2 discusses the labour share in the Netherlands in greater detail. Chen et al. (2017) explore factor share in global value chains and find that independent of countries, labour shares have declined in many production processes by shifting labour costs to low wage countries.

The measurement debate furthermore deals with other issues. Rognlie (2016) shows that labour shares outside the housing sector have remained much more stable and Bridgman (2017) suggests rising depreciation costs might account for some of the fall in labour shares. A rising share of depreciation in gross income would indicate that factor shares have remained more stable in net terms. These measurement issues are relevant as they might explain (part of) the labour share decline, as well as the shifts in the income shares of other factors. If the observed factor share changes are due to changing relevance of measurement errors, and/or due to a rising share of depreciation, the net income distribution might have remained stable, perpetuating Kaldors "remarkable historical consistency".

The second part of the literature focusses on the drivers of factor income distribution changes. These changes signal that production technology at a fundamental level might be changing. Particularly, it could be an indication that the elasticity of substitution between (in-

[2]See for example Krueger (1999), Elsby et al. (2013), Karabarbounis and Neiman (2014), and Blanchard and Giavazzi (2003)

tangible) capital and labour has risen to a level higher than unity (Piketty, 2015; Karabarbounis and Neiman, 2014; Acemoglu and Restrepo, 2018b). This means that as capital becomes more abundant and prices are reduced, the (intangible) capital share is likely to rise.

Even if the elasticity of substitution has not risen, as some authors maintain (Oberfield and Raval, 2014; Barkai, 2016), a decline of the labour income share indicates production technologies might be changing. Such technological changes are further reflected in several other developments that happened concurrent to the changing factor income distribution. For example, declining of business dynamism (Akcigit and Ates, 2019), rising firm mark-ups (price over marginal cost) (De Loecker et al., 2018a) and sluggish investment rates (Philippon, 2018).

The drivers of factor income share changes tend to be the focus of most related literature, not in small part because of the myriad of potential drivers potentially responsible. However, much of the literature has focussed almost exclusively on the changes in the labour share. While an interesting development, it seems to me the discussion ought to be wider. Figure 1.2 illustrates this by showing that while the labour share has indeed been on a declining path, the developments of non-labour income are more pronounced. Chapter two of this dissertation shows that for the Netherlands, the labour share has been virtually stable over that past two decades, yet chapter three shows that the non-labour income shows much more dynamics.

The developments of the non-labour income have not been emphasised as much in the literature. Barkai (2016) shows that in addition to labour, the tangible capital share has also declined in the United States over the last 30 years. He argues that a less competitive industry environment is the cause of this shift. Put simply, less competition allows firms to charge higher prices raising their economic profits, which are not derived from the use of any production factor.

Autor et al. (2019) formalise the competition-based argument in a model focussed on so-called 'superstar' firms. The details of their argument are presented in chapter 2, but in short, they propose that large and productive (superstar) firms are increasingly expanding their market share. These superstars tend to have low labour shares, so their rising prominence reduces labour shares at the national level, but also internationally (Autor et al., 2019).

This superstar hypothesis offers a micro-founded mechanism of how factor shares might have shifted, but it does not answer the question why, or rather, what has fundamentally changed to drive the changes. This is a question that the large labour share literature, as well as the discussions in the subsequent chapters, weigh in on. A common theme throughout most arguments is, perhaps unsurprisingly, technology.

Rapidly advancing technologies have become increasingly ubiquitous both in daily life and in the production processes of firms, particularly IT (Brynjolfsson et al., 2008, 2018; Aghion et al., 2019). Weir (2018) posits that the uneven take-up of IT between firms increases the heterogeneity in productivity and growth rates between them. Similarly, Aghion et al. (2019) argue that IT has allowed productive firms to expand into more product lines. These forces might have ushered in the heterogeneity between firms required for superstars to arise.

Karabarbounis and Neiman (2014) found the elasticity of substitution between capital and labour to be larger than one, in line with declining prices of (IT) capital inputs being negatively related to labour shares. They argue technological change has suppressed the price of certain types of capital, pushing firms to opt for more capital-intensive forms of production, while reducing labour intensity. Similarly, a growing related literature regards the role of automation, which envisions capital directly taking over tasks previously performed by human workers; Acemoglu and Restrepo (2018a) and Autor and Salomons (2018) show such effects could reduce labour shares.

Closely related to the developments of technologies is the rise of intangible capital. The rising importance of intangibles can explain labour and tangible capital share declines (Koh et al., 2019). The argument is that the rewards to these assets would have captured a larger share of GDP, given the right elasticities of substitution, and the large increase in investments into intangibles (Corrado et al., 2005; Haskel and Westlake, 2017). This could have been through the same superstar effects as described above with larger, more productive firms adopting more intangible intensive production (De Ridder, 2019). Chapter 3 explores the issue of intangibles in some depth, and reviews how well they might account for the rise of factorless income illustrated in 1.2.

More indirectly, new technologies like ICT and intangible assets could influence factor shares through globalisation. Globalisation, and specifically offshoring of production have been found to correlate negatively with labour shares (Elsby et al., 2013; Resheff and Santoni, 2019; Guscina, 2006; Harrison, 2005). In particular, Elsby et al. (2013) argue that offshoring can drive down labour shares by shifting labour-intensive production stages to low wage countries. This means production stages left behind are less labour intensive, reducing the aggregate labour share.

Chen et al. (2017) hypothesize that due to offshoring, the income share accruing to intangibles has increased. They suggests that increasingly internationalized production processes shift towards more intangible-intensive production, both within countries and throughout the (global) value chains (Timmer et al., 2014). At the same time, certain coordination and communication-related intangibles are more valuable in geographically dispersed production processes (Chen et al., 2017). Chapter three provides an exploration of offshoring and factorless income.

1.3 Thesis Outline

This section outlines the contents of this thesis. Chapters two, three and four are based on three different projects that I have worked on during my PhD. These contribute to the literature in different ways but are related to the topics introduced above. Chapter two is based on the paper "Superstar dynamics at work: Firms and the labour income share in the Netherlands". My co-author and I use detailed firm-level data to explore the dynamics underlying labour share changes in the Netherlands. We decompose the developments of the labour share into within and between-firm dynamics and relate these labour share developments in several industries to superstar firm dynamics. We find that superstar dynamics play an important role for a group of about one-quarter of all industries in the Netherlands. These industries experience labour share declines, while others tend to have more stable or even increasing labour shares.

The third chapter is based on my paper "Factorless Income in a Globalising World; Measurement and Analysis". There, I explore the evolution of factorless income across a set of developed countries. This requires unpacking GDP into its components as shown in figure 1.1. I start by documenting the changes in the factor income shares. Subsequently, I find that a sizeable share of factorless income remains, after labour and tangle capital income have been accounted for. I furthermore establish that intangible assets cannot account for all of the factorless income share, with currently available data. Finally, I link the factorless income share to globalisation to demonstrate that the two are correlated.

Chapter four is based on the paper "Natural resources and missing inputs in international productivity comparisons" which, at the time of writing, is forthcoming in the Review of Income and Wealth. The chapter focusses on cross-country productivity comparisons. In particular, we focus on the role of natural capital in these comparisons. In this paper, my co-authors and I develop an extension to the established methodology. This extension allows us to account for natural capital assets, which is important to accurately document productivity differences across countries.

1.3.1 Superstar Dynamics in Dutch Industries

Recent work on factor share changes indicates that much of the factor income dynamics occur at the level of firms, where changes of the aggregate factor shares are driven mostly by the largest firms. In the second chapter, therefore, my co-author and I zoom in on the Netherlands and explore the firm-level dynamics within industries. We investigate which firms contribute to share declines, and evaluate their performance concerning market power, productivity, and output. In particular, we focus on the role of industry environments in enabling these dynamics. This chapter is closely related to similar work done for the United States (Kehrig and Vincent, 2018; Autor et al., 2019).

The chapter presents a detailed analysis of the firm-level dynamics underlying the Dutch aggregate labour share change over the period 2000-2015. We approach this matter with a primary hypothesis in mind; the superstar hypothesis. According to the superstar hypothesis, large, highly productive, and low labour share firms are becoming more dominant in their industries and accrue more market power. The rise of these firms would reduce industry labour income shares because these firms tend to have lower labour shares. This mechanism has recently gained a lot of traction in the literature through works such as Autor et al. (2019) and De Loecker et al. (2018b).

Consider a particular industry for which we have found superstar dynamics to be relevant; travel agencies. Across the globe, several relatively new firms have recently been dominating nearly every aspect of the travel industry[3]. In particular, the way many people arrange their travel now, compared to twenty, or even ten years ago is drastically altered. The ease with which different travel options can now be found, evaluated, and compared over the internet has revolutionised our holidays and other travels.

The days that consumers would consult a travel agency, which would then arrange the full aspect of a holiday or business trip, appear to be fading. Instead, we now consult several huge online platforms that automatically select the travel options best suited to our preferences[4]. The shift of business away from traditional travel agencies, towards these platform firms, illustrates exactly what the superstar mechanism entails for industries. These few platform firms

[3] For example, Airbnb, Uber, Skyscanner, Priceline (Booking.com)

[4] See Cennamo and Santalo (2013); Economist (2005) for more on the platform economy.

have leveraged specific technology, information and organisational intangibles to realise rapid productivity growth, and in doing so have captured large shares of their market.

The contribution of this chapter is to point out important heterogeneity in firm dynamics across industries. In line with the flat aggregate labour income share trend, we find no evidence for a country-wide superstar effect. Instead, we focus on firm-level characteristics and developments and we find superstar dynamics are present in ten industries, among which the travel agency industry, but not in the remaining 43 industries we examine. Using an Olley and Pakes (1996) decomposition we see that market share reallocation between firms puts downward pressure on labour shares in the industries with superstar dynamics, but not in others.

These findings show that (limited) superstar dynamics are present, but also explain why these dynamics have not led to declines in the aggregate labour income share since 2000. This suggests that superstar dynamics only flourish in particular environments provided in a limited set of industries in the Netherlands. This opens up a path for future research to explore the factors conducive to industry superstar dynamics in more detail.

1.3.2 Factorless Income Dynamics

The decline of the share of labour since the 1980s is well documented in the literature; however, increasing evidence suggests that the income share of tangible capital has also been declining during the same period. In the third chapter, I investigate the rise of factorless income, which cannot be attributed to either tangible capital or labour. This rise means a relative shift of income away from workers and owners of tangible capital, but to whom this income goes remains an open question. To explore this, the first step is to accurately estimate the income shares of labour and tangible capital, which requires a series of choices and assumptions, which I discuss and evaluate at some length.

According to Karabarbounis and Neiman (2018), the factorless income share can be accounted for in three ways. These are economic profits, un/mismeasured capital stocks, and an increasing level of risk in capital investments. Likely, only a combination of these can fully account for factorless income, but the second case is of particular interest in the context of this thesis. The unmeasured stock of capital could be a stock of *in*tangible capital, many assets of which are not accounted for in national accounting frameworks.

Using the INTAN-invest intangibles data (Corrado et al., 2016), I integrate intangible assets into the framework as additional production factors. The results show that this yields a smaller estimated rise of factorless income. However, significant variation between industries and countries remains both in terms of the rise and levels of the factorless income share. It is possible that the intangible assets from this data do not adequately measure intangible assets or do not cover all relevant types.

To explore this possibility, I follow Chen et al. (2017) in hypothesising that increasing international trade integration has played an important role in the formation of the stock of intangibles assets, and the rise of factorless income more generally. I relate the change of the factorless share to the developments of offshoring and import competition at the country-industry level.

The results show that offshoring has contributed to driving up the factorless share. Import competition has the opposite relation; more of such competition is associated with lower factorless income. This could indicate a negative relation between import competition and firm mark-ups, which are often part of factorless income.

Finally, I find evidence that globalisation and the investment in intangibles are positively related. This relation suggests factorless income dynamics might (at least partially) be driven by globalisation through the effects it has on investments in intangible assets. More detailed information is required to make more definitive conclusions. My current analyses, with the current data, are not sufficient to account for factorless income and its dynamics fully.

1.3.3 Cross-Country Productivity Comparisons & Natural Capital

In the fourth and final chapter of this thesis, my co-authors and I seek to establish a method that modifies the standard Diewert and Morrison (1986) framework for cross-country productivity comparisons. The aim is to address a problem facing such comparisons, which arises when some country completely lacks specific input factors. In this case, productivity comparisons become impossible because the methodology does not allow for zero-inputs.

We propose a novel and theoretically-grounded method that allows us to make productivity comparisons between countries, even in the case that some inputs are not available in certain countries. We illustrate our method for a broad sample of countries by incorporating natural resources into the production function as productive inputs. As not all countries are endowed with all natural resources, this example is well suited as a demonstration.

More generally, the standard methodology breaks down when quantities of inputs are zero and prices are undefined. Our revised method uses counterfactual prices for missing inputs, based on producer Hicksian reservation prices. These are set such that demand for a missing primary input would have been zero has it not been missing. Additionally, we treat these inputs as intermediate, rather than primary inputs in countries with positive endowments. This allows us to adjust the comparison by subtracting resource rents in the country with positive endowments from total output. This enables us to make a productivity comparison between two countries with different sets of primary inputs, without running into the missing input problem.

The results show that the method can be applied in practice, and is highly relevant for several countries with large endowments of natural capital, most notably oil-producing countries. For these countries, productivity estimates compared to the U.S.A. are adjusted significantly downward. To evaluate the efficiency with which inputs are utilised can yield valuable insights into the origins of income differences between countries. Our method is a step toward improving our ability to uncover the origins of these differences by allowing for more accurate comparisons.

In terms of this dissertation, the chapter shows the importance of accounting for a set of inputs that is as complete as possible. In our productivity comparison exercise, natural capital is an important input for some countries. We show that omitting it leads to biased relative productivity estimates. Such a missing factor bias affects any comparison of productivity or other exercise that relies on accounting for the income generated by production factors. Particularly, similar issues are likely arise when intangible capital is not accounted for.

1.3.4 Conclusions

In this dissertation I have shown three developments important to the changing factor income distribution. First, the rise of superstar firms, and more broadly the changing nature of competition. Second, the increasing share of income made up of returns from intangible assets. Third, increasing globalisation and the internationalisation of the production process. Furthermore, I have stressed the measurement of income shares and demonstrated its relevance at the firm, industry, and country levels for exploring these three relations.

These developments may lead to increasing income inequality because of declining income shares of more equally distributed production factors. This means that larger shares of income are accruing to fewer firms and people, in particular to those in control of the intangible assets. Large superstar firms, especially those operating globally, likely benefit the most from intangible assets. This is because they have the (global) scale that allows them to invest in, and most effectively reap the benefits from intangibles.

A major source of the superstar firms' dominance appears to be ICT, as borne out by highly successful platform firms. Advancing technologies in the future might further increase superstar firms' market power and control over global markets. Superstar firms might therefore become increasingly dominant, and relevant for more sectors of the economy. This will likely speed up the shift away from labour and tangible capital, towards intangibles.

With this, my dissertation has paved the way for future research to consider how current and future technological advances will shift income across countries, factors, firms, and people. Such future work can build on the insights presented in my dissertation to document and evaluate the changing factor income distribution, ensuring that inequality outcomes can be identified and perhaps ameliorated.

Chapter 2

Superstar dynamics at work: Firms and the labour income share in the Netherlands

2.1 Introduction

Since the 1980s, the labour share of income declined across a wide selection of countries and industries. Research investigating the developments of the aggregate labour income share have found for the United States that it has declined 4-5 percentage points (ppt) since the 1980s (Barkai, 2016; Elsby et al., 2013; Piketty, 2015; Dao et al., 2017). Not all countries have experienced such strong labour income share declines and some countries have had stronger declines still, but many authors agree it is a broad-based phenomenon across the developed world (Karabarbounis and Neiman, 2014; Autor and Salomons, 2018), and beyond (Dao et al., 2017).

The labour income share decline has sparked the interest of many economists partly because of the empirical 'Kaldor-fact', which states that income shares remain stable over time (Kaldor, 1957). Various approaches are used in the literature to explain the origins of labour income share dynamics, with varying degrees of success, these are discussed in more detail below. Specifically, spearheaded by Autor et al. (2019), one of these approaches examines the labour share at the level of individual firms. This approach is motivated by the finding that the declining labour income share appears to be a development within industries (Elsby et al., 2013; Karabarbounis and Neiman, 2014; Rognlie, 2016). For this reason, the firm-level dynamics and developments of labour share must be relevant.

The firm-level research has found considerable heterogeneity between firms in terms of their labour shares, and relevant dynamics. The downward labour income share trend in many industries is ascribed to the reallocation of market share between firms. This means that the aggregate decline of the labour income share is driven by the increasing market shares of firms with lower-than-average labour shares. Some of the literature focusing on the United States has found reallocation between firms is due to a small number of productive firms with high market power– the so-called 'superstar firms'. These superstars have succeeded in expanding their market shares without proportionally increasing their wage bill, and in so doing reduced the aggregate labour income share (Autor et al., 2019; Kehrig and Vincent, 2018).

This superstar mechanism is described in more detail in Autor et al. (2019). The authors introduce a superstar firm model to explain declining labour income shares. Their model predicts that superstar firms compete other firms away, and therefore increasingly capture larger parts of the market. Because superstar firms increase their market shares, aggregate labour income shares fall and similarly, aggregate mark-ups and productivity increase[1]. These dynamics char-

[1]Productivity increases in the short-run at least, De Loecker and Eeckhout (2018) and De Ridder (2019),

acterise the superstar mechanism, and we use them to evaluate the presence of this mechanism within individual industries in the Netherlands.

We contribute to the literature by using an extensive dataset covering all non-financial corporations in the Netherlands, to explore the superstar firm dynamics underlying labour income shares changes in Dutch industries. Specifically, despite a stable aggregate trend, we find that industry-level labour incomes share developments display a large degree of heterogeneity. In line with the aggregate labour income share trend, we find no evidence for a country-wide superstar effect, which is in contrast with the finding for the United States (Autor et al., 2019; Kehrig and Vincent, 2018). Instead, we focus on enterprise-level characteristics and developments and while we do in fact find superstar dynamics, they are only present in 10 of the 53 industries we investigate.

Finally, using an Olley and Pakes (1996) decomposition we see that market share reallocation between firms puts downward pressure on labour shares in the industries with superstar dynamics, but not in others. This means that (limited) superstar dynamics are present, but also explain why these dynamics have not led to declines in the aggregate labour income share since 2000. Our findings suggest that superstar dynamics only flourish in particular environments present in a limited set of industries in the Netherlands. This opens up a path for future research to explore the factors conducive to superstar dynamics in more detail.

This chapter is related to the literature attempting to explain the decline of the labour income share, as discussed above. Grossman et al. (2017) and Weir (2018) provide useful overviews of this literature. More specifically, this chapter is embedded in the literature that uses microdata to explore labour income share dynamics (Autor et al., 2019; Kehrig and Vincent, 2018).

This chapter uses insights from the literature on heterogeneous firms, which we use in the estimation of key variables (Lucas Jr, 1978; Hopenhayn, 1992). We use the work by among others Olley and Pakes (1996) and Wooldridge (2009) for our decomposition and productivity estimation. This work is furthermore related to the literature which has arisen around the estimation of firm mark-ups, spearheaded by De Loecker and Warzynski (2012) and De Loecker et al. (2018a).

Linked to this is the literature about the competitive environment of firms, which points to a decline of the competitive dynamism in many industries (Decker et al., 2017). Akcigit and Ates (2019) point to ten different changes in industry dynamics in the United States, including declining labour income shares. Likewise, various authors point out that the concentration ratios of industries in the United States have been increasing (Philippon, 2018; Gutiérrez and Philippon, 2017; Decker et al., 2018). Particularly, many of these developments, along with the rise of superstar firms, seem to coincide with the decline of the labour income share (Autor et al., 2019).

An explanation for the market share shifts that enable superstar firms is provided by Akcigit and Ates (2019). They document a series of indicators of declining business dynamism and suggest that uneven distribution of knowledge and a decline in knowledge diffusion might be responsible. Weir (2018) and Hsieh and Rossi-Hansberg (2019) argue that the origins of the

among others show that despite short-run gains, this dynamic can lower long-run productivity growth.

superstar mechanism might be rooted in uneven take-up of IT, automation and other new technologies with high fixed cost. A comparable argument can be made for the uptake of intangible capital, like software, R&D, and organisational capital (De Ridder, 2019). Uneven uptake of new technologies and intangibles between firms increases dispersion in firm productivity, and marginal costs, allowing some firms to attain larger market shares (Faggio et al., 2010; Brynjolfsson et al., 2018). Due to the high fixed cost of IT and intangibles, the most productive firms benefit relatively more from investing in them. Through such investments, these firms realise additional productivity growth and expand output without increasing their labour costs correspondingly, thanks to technological or intangible assets and simply due to firm size (OECD, 2018; Brynjolfsson et al., 2008; Acemoglu and Restrepo, 2018a).

Various sources provide evidence of the link between new technologies and labour income shares. Karabarbounis and Neiman (2014) find declining prices of (IT) capital to be correlated with labour income share declines[2]. Acemoglu and Restrepo (2018a) and Autor and Salomons (2018) propose task-based frameworks that allow labour displacing technologies to reduce its income share. Further evidence comes from Adrjan (2018) who finds a negative relationship between capital intensity and labour shares of firms in the United Kingdom, in addition to finding a negative correlation between firm labour income shares and their market shares.

Of course, a wide array of different topics related to labour income share declines have been examined. These range from labour market regulation (Blanchard and Giavazzi, 2003; Ciminelli et al., 2018), offshoring (Elsby et al., 2013; Resheff and Santoni, 2019), and intangibles (Dao et al., 2017; De Ridder, 2019).

Most of the current literature on these topics focus on the United States. Labour income share research for other countries has been done less frequently. However, some authors do note some differences between continents in terms of the relevant developments. Döttling et al. (2017) and Guschanski and Onaran (2018) find that European industry concentration is lower and increasing less rapidly than in the United States[3], suggesting that rising market power might play a smaller role in European countries. Gutierrez (2017) finds systematic differences between declining labour income shares in the United States and the rest of the advanced world, and Cette et al. (2017) argue that in some advanced countries, there is no decline at all. For the United States, the labour income share decline is found across most sectors of the economy, while elsewhere, it is limited to specific sectors. Furthermore, McAdam et al. (2019) point out the differences between the United States and Europe in terms of mark-ups, concentration, and industry dynamism.

Considering the Netherlands specifically, van Heuvelen et al. (2018) find that the most productive firms in the Netherlands do not correspond well to the image of superstar firms. They find that firms at the national productivity frontier are not consistently large or dominant players. Likewise, van Heuvelen et al. (2019) find only very limited or no increase in the aggregate mark-ups in the Netherlands. At the same time, Deelen et al. (2018) highlight the importance of within-firm changes of labour shares in the Netherlands, rather than reallocation

[2]Some subsequent literature has questioned their finding of an elasticity of substitution larger than unity; Oberfield and Raval (2014) present a strong case it is smaller than one. Though other literature has argued that even if this is not the case, the adoption of new technologies can still be linked to declining labour shares(Acemoglu and Restrepo, 2018a; Autor and Salomons, 2018)

[3]Calligaris et al. (2018) find differences even between European countries in this regard.

between firms as the superstar mechanism posits[4]. Additionally, they find indicative evidence that mark-ups and automation are related to the development of the firm-level labour shares in the Netherlands. DNB (2018) furthermore finds tentatively that the decline in the labour income share can be linked to an increase in flexible labour contracts. These findings illustrate that there are both similarities and differences between the Netherlands and the United States in terms of the labour income share changes and related developments.

This chapter continues as follows; in the next section, we present the firm-level data. We focus on the distinction between different industries and show the disparity in labour income share changes across industries, some have experienced major labour income share declines, but many others have not. In addition, we derive several measures of the superstar mechanism that help us evaluate the relevant firm dynamics within industries. Following the superstar hypothesis, we estimate measures of productivity and market power. For productivity, we estimate firm-level TFP, which is standard in the literature. We use firm-level mark-ups as our preferred measure of market power (McAdam et al., 2019; Calligaris et al., 2018; De Loecker and Warzynski, 2012).

In the third section, we divide the data into groups depending on the firm-level relation between productivity and market share growth. We continue to verify that all superstar firm dynamics are stronger in the group with a positive productivity-market share growth relation. This suggests that particular market environment conditions must be met for superstar dynamics to be relevant, which appear in a limited set of industries, but not across the economy. Using these two groups of industries, we employ the Olley and Pakes (1996) decomposition, which reveals reallocation is important for labour income share dynamics in industries with superstar dynamics, but not in the other industries. In the fourth and final section, we discuss the results in more detail and conclude.

2.2 Measurement & Descriptives

2.2.1 Labour Income Share

The data is primarily based on the NFO (Non-Financial Enterprises[5]) dataset administered by Statistics Netherlands. It contains detailed enterprise-level balance sheet data on all corporations in the Netherlands, specifically featuring data on output, various inputs and costs relevant for our analyses[6]. The full dataset covers the period 2000-2016 and the entire corporate sector of the Netherlands, excluding the financial sector. All of the firms are equipped with industry identifiers at the 2-digit ISIC rev. 3 level[7]. We link the NFO data to the POLIS dataset, which contains information on employees. From this data, we obtain worker wages and hours worked to estimate the production function introduced below. Unfortunately, this latter dataset is only available starting 2006.

[4]They use a value added weighted within term, which prioritises larger firms.

[5]"Niet-financiele organisaties" in Dutch.

[6]Throughout the chapter we refer to enterprises as 'firms'.

[7]The actual system is the Statistics Netherlands SBI (2008) system, which is equivalent to ISIC at the 2-digit level. Furthermore, this data can be linked to the business registry data (ABR) to obtain more detailed classification, as well as firm, rather than enterprise-level identifiers.

The firm-micro data allows us to examine the period 2001 through 2015, leaving out the first and last year of data availability due to quality concerns[8]. We remove the smallest firms from the data, leaving only firms with more than one FTE, other selection choices and cleaning of the data is elaborated on in the appendix. The final sample contains between 100,000 and 130,000 firms per year, for a total of roughly 300,000 starting in 2001, and 250,000 between 2006 and 2015[9]. Using these data, equation (2.1) shows how we construct the labour income share of firm i at time t. LAB_i is the labour cost, and VA_i is gross value added[10] of firm i. These are computed in nominal values.

$$S_{it} = \frac{LAB_{it}}{(VA_{it})} \tag{2.1}$$

Figure 2.1 shows the labour income share changes of the industries in our data. Firstly, the figure shows a large variance in labour income share changes across industries. Several industries have experienced strong declines, while others saw labour income share increases. The aggregate national labour income share trend has been relatively flat during this period (Deelen et al., 2018), but the same cannot be said for individual industries. This sets the developments of the labour income share in the Netherlands apart from other countries and specifically the United States, where it has declined strongly in most industries over the same period (Autor et al., 2019).

2.2.2 Mark-ups & TFP

Here we outline the methods we use to derive measures for firm market power and productivity. The fact that the Netherlands is a small open economy is important for the market power indicator. Previous literature has used concentration as a measure of market power (Autor et al., 2019), However, using concentration-based measures for the Netherlands is more difficult as many markets are highly dependent on international trade. As such, concentration measures based on domestic output will miss much of the competition dynamics (from abroad) facing firms. In addition, concentration might also be misleading when the threat of new firms entering the market is particularly high, or when examining an inappropriate geographical area (Calligaris et al., 2018; Rossi-Hansberg et al., 2018). Furthermore, concentration is an industry-level measure, while our analysis calls for a more detailed, firm-level measure.

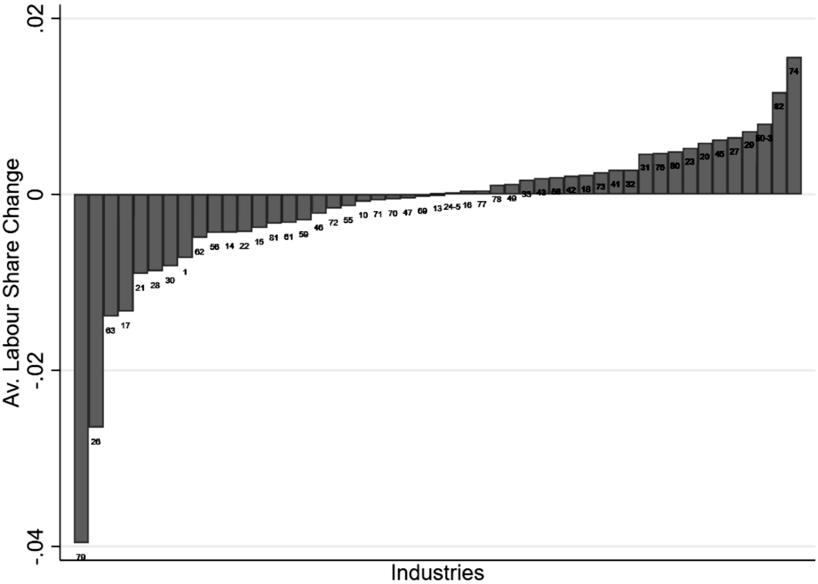
To circumvent these problems, we use firm-level mark-ups as our preferred measure of market power. To illustrate its validity, increasing competition will leave firms less opportunity to charge a price above their marginal cost as competitive forces drive down prices. Therefore, a declining mark-up is likely a signal of increasing competition in a market and of declining

[8]For 2000 the number of firms and the size- make-up differs strongly from subsequent years. For 2016, the number of imputed data points in the current data release leads us to leave it out of consideration.

[9]This is not quite the same number as previous work like van Heuvelen et al. (2018), primarily because we drop the smallest firms, as including the labour income share for very small firms and the (de-facto) self-employed raises issues that could distort the aggregate labour income share (Gollin, 2002).

[10]Where value added is the difference between net revenue and intermediate inputs. Revenue is sales less product-specific taxes; intermediates include all inputs and costs not relating to wages, interest payments, and depreciation. Importantly, intermediates include costs of indirectly hired persons or contract work. This means that our measure labour cost does not include the costs associated with this type is labour.

Figure 2.1: Labour income Share, 2001-2015 annual change across industries



Note: Each bar represents the industry average labour income share change (weighted by firm value added) over the period 2001-2015. The industries are ranked by labour income share decline. The numbers indicate annual percentage-point labour income share changes, this means that the largest annual decline of almost 4%, the total decline over the period 2001-2015 has been 56 percentage points. Note industries 24-25 and 50-53 have been collapsed to avoid breaking data confidentiality rules.

market power[11]. Note that mark-ups do not necessarily reflect firm economic profits. Rising mark-ups might be indicative of firms using higher fixed-cost methods of production, which entail low marginal costs, but require higher mark-ups to recuperate high up-front investments. Using mark-ups, we obtain a firm-specific measure of market power, which does not suffer as strongly from the aforementioned problems[12]. In the same estimation, we estimate total factor productivity (TFP), our measure of firm productivity.

To estimate mark-ups and TFP, we require a production function that specifies the relation between inputs and outputs. We choose to use a gross output function to obtain the output elasticity of materials, which we need for the estimation of mark-ups, as expanded on below. TFP is estimated as a productivity residual, which can be interpreted as the efficiency with which a firm uses its inputs to produce output. Autor and Salomons (2018) interpret TFP as an indicator for automation and adoption of technology.

Equation (2.2) shows the production function we estimate; we estimate this function for each industry[13]. q is output, k, l, and m, are the logs of capital, labour and materials, and the β's represent the output elasticities of each input. To estimate this function, we use firm-specific information on the deflated total revenues, capital stock, labour, and materials input values. Our labour input variable is the total hours worked by employees of the firm and we use hourly wages as an instrument, both as advocated by Gandhi et al. (2017). Because these variables are only available from 2006 onwards, we focus on analysing the 2006-2015 period whenever TFP and mark-ups are used in analysis[14]. The estimation of the production function utilises the Wooldridge (2009) one-step procedure[15].

$$q_{it} = a + \beta^K k_{it} + \beta^L l_{it} + \beta^M m_{it} + \epsilon_{it} \tag{2.2}$$

From this estimation, we obtain each firm's TFP ($a + \epsilon_{it}$) as a productivity residual. The overall TFP shows an upward trend, but there is some strong variance between different industries as illustrated by their changes shown in table 2.3. Mark-ups are estimated using the methodology introduced by De Loecker and Warzynski (2012), based on Hall (1988) and popularised among others by De Loecker et al. (2018a). The mark-up is derived as per equation (2.3), where μ_{it} is the mark-up for firm i at time t. β^M_{ct} is the output elasticity of the variable input specific to firm i's industry c, estimated using equation (2.2). $P^Q_{it} Q_{it}$ and $P^M_{it} M_{it}$ are the value of total output and the variable input materials[16].

[11] At the same time, on the industry level another story is possible. Specifically, if competition favours the most productive firms, who can charge higher than average mark-ups, industry-level mark-ups could be increased by more competition. This is because the most productive firms will be increasing their market share, which would positively affect industry mark-ups due to a reallocation effect. In either case, an increase in mark-ups signals an increase in market power on average in an industry.

[12] The firm balance sheet consolidation level might still play a role. Our data uses balance-sheet information at the national level, if firms themselves are heavily involved with operations abroad, some measurement error might creep into our mark-up due to transfer pricing.

[13] In fact, we estimate it twice for each industry, where we estimate each output elasticity for large ($> 75^{th}$ percentile) firms and smaller firms separately.

[14] One way around this problem is use labour costs instead of labour hours, which might lead to biased estimates, we present results using such estimations as a robustness check below.

[15] We refer the reader to van Heuvelen et al. (2018) and van Heuvelen et al. (2019) for further details on the production function estimation with our data.

[16] This method relies on a firm's variable input because it most closely approximates the marginal cost of production, as opposed to non-variable inputs like capital, which are subject to (unobserved) adjustment costs.

$$\mu_{it} = \beta_{ct}^{M} * \frac{P_{it}^{Q} Q_{it}}{P_{it}^{M} M_{it}} \tag{2.3}$$

This equation follows from the FOC of the variable input and defining mark-ups as the price over marginal costs. We can estimate the mark-up by multiplying the output elasticity of a variable input, by the inverse of that input's cost-share, as shown in equation (2.3). The appendix expands further on the derivation of the mark-ups.

To obtain mark-up estimates we need to estimate the output elasticity of a variable input. Various approaches in the literature estimate mark-ups by using a combination of materials and labour as variable inputs, mostly due to data constraints (De Loecker et al., 2018a; Traina, 2018). We choose to use materials as our variable input for two reasons[17]. First, labour markets in the Netherlands are rigid, therefore prefer not to include labour as a variable input. Second, since we aim to relate mark-ups to the labour income share, it would not make sense to use the inverse labour cost share in our mark-up estimation, lest we impose mechanically a negative relation between the two. Therefore, to estimate mark-ups we use the gross output function because estimates the output elasticity of materials[18].

Having derived firm labour income shares, and estimated measures of productivity and market power, the next section uses them to evaluate the presence of superstar dynamics in the Netherlands. First, we will look at the aggregate level, followed by an exploration at the industry level.

2.3 Superstar Firms and Dynamics

In this section, we evaluate the superstar mechanism for the Netherlands at an aggregate level and for individual industries. The mechanism contains firm-level dynamics that lead to declining aggregate labour income shares and is hypothesised to be (one of) the driving force(s) of labour income share declines in the United States (Autor et al., 2019). The mechanism works by low labour income share superstar firms expanding their market share through high market power. This reallocation of market shares toward low-labour income share firms reduces aggregate industry or even national labour income shares.

Autor et al. (2019) define a superstar firm as a *highly productive* firm with *high mark-ups* and a *low labour income share*. They suggest that such firms can become more dominant because markets are increasingly "winner-take-most", or the most productive firms increasingly have an advantage over less productive ones. They hypothesise this could be due to globalisation, easier price comparisons through the internet, platform firms, or other developments that might have increased consumer price sensitivity. Whichever development is driving this new dynamic, it is benefiting the most productive firms, which can more easily outcompete their rivals in an environment where small price differences can mean the difference between success and failure.

Given this definition of superstar firms and the description of the superstar mechanism,

[17] Note that the labour inputs of contractors are included in the materials in our data.

[18] The literature has put forward a wealth of possible production functions and other choices that need to be considered when estimating production functions and mark-ups, see van Heuvelen et al. (2019), where some of the alternatives are discussed.

several firm-specific characteristics and dynamics should be observable in the data. First, we expect *(1) productive firms have high market shares.* If this were not the case, and productive firms are not larger than others, any superstar dynamic would have little effect on aggregate labour income shares. Second, we expect superstar firms to have higher market power. Our measure of market power is mark-ups, so we expect *(2) productive firms have higher mark-ups than other firms.* Thirdly, as explained above, we expect to find that *(3) productive firms have lower labour income shares than other firms.*

The superstar mechanism posits that aggregate labour income shares are reduced due to the most productive firms accruing more market share. This dynamic reduces aggregate labour income shares because superstar firms have lower labour income shares. Therefore, we expect to find in the data that *(4) productive firms are more likely to grow their market share.* This has three consequences: given the presence of superstar dynamics, we expect to see (i) rising aggregate productivity, (ii) rising mark-ups, and (iii) declining labour income shares. All three are directly due to reallocation of market share towards superstar firms, away from other firms. We will return to these consequences in the next section.

We evaluate predictions *(1)-(3)* by running regressions relating productivity to the various other indicators. To start exploring these relationships, we regress initial TFP on the initial values of the value added market share[19], mark-ups, or labour income shares. Equation (2.4) shows the regressions that we use. TFP^1 is a firm's initial TFP value in 2006, or when it entered the data, and X_i^1 the initial value of the independent variables; value added market share (VAS), labour income share, or mark-up.

Note that the regressions presented in this section are weighted by firm market shares. This means that every industry is weighted equally, and each firm is weighted by its prominence in that industry. This ensures that two firms in different industries, which might differ strongly in size, gain equal weights if they have the same market share in their respective industries[20].

$$X_i^1 = \alpha_0 + \alpha_1 TFP_i^1 + \nu_x + \epsilon_i \tag{2.4}$$

We evaluate prediction *(4)* by examining whether productive firms are more likely to gain market share than other firms. Equation (2.5) lists the regression we use to analyse this question. TFP_i^1 is again the initial firm productivity when it first enters the data, and ν_x are industry fixed effects. ΔVAS_i is the change in value added market share (VAS) over the period 2006-2015 or the period during which firm i is represented in the data if it differs[21]. We estimate the odds of a firm gaining value added market share given its initial TFP using logit regression.

$$Pr(\Delta VAS_i > 0) = \beta_0 + \beta_1 TFP_i^1 + \nu_x + \epsilon_i \tag{2.5}$$

[19] Note that we use the market share in value added as this concept fits the labour income share measure. Alternatively, output-based market share would work less well, as firms with high shares of intermediate inputs might cloud the results.

[20] This assumption is important for the results we find. If the regressions are run unweighted, the strength of the findings is reduced. This is because the data features many small firms, which obscure the superstar dynamics featuring mostly the largest firms in each industry.

[21] Firms that only appear once in the sample are coded zero, for not attaining growth. Not considering these firms does not affect the results, however.

Table 2.1: Regression results

VARIABLES	(1) Value Added Market Shares (Initial)	(2) Mark-Up (Initial)	(3) Labour Share (Initial)	(4) Pr(ΔVAS>0)
TFP (initial)	0.0736***	0.583**	−0.144***	−0.633***
	(0.00660)	(0.0447)	(0.0104)	(0.0987)
Constant	−0.1000***	0.804***	0.763***	0.315**
	(0.00919)	(0.0706)	(0.0167)	(0.156)
Observations	242,312	242,312	242,312	242,312
R-squared	0.634	0.098	0.258	
Industry FE	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The table shows the regression results from estimations using equations (2.4) and (2.5), each firm observation is weighted by the average value added market share over its lifetime.

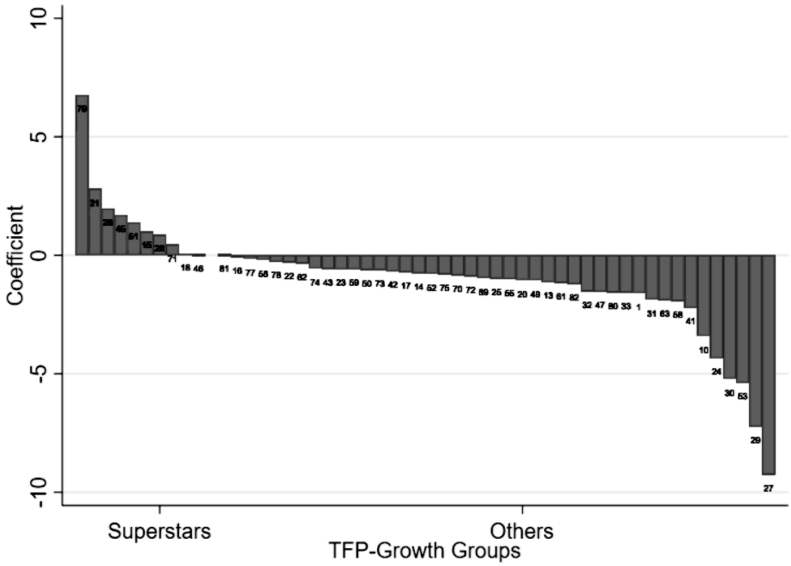
Table 2.1 shows the results of these regressions. All regressions shown are at the firm-level and weighted with average firm value added market share (over their lifetime). The first three columns show the results of estimating equation (2.4), exploring the presence of the superstar firm characteristics. All three associated expectations are borne out in the data. More productive firms tend to have larger market shares, higher mark-ups, and lower labour income shares. Completing table 2.1, column four shows that on average, higher productivity firms are associated with a lower chance of gaining market share. This means the fourth prediction, which posits that productive firms are *more* likely to gain market share, appears not to hold in the data.

The first three columns indicate that firms with superstar characteristics might be relatively common. However, the final result indicates that on average, no superstar dynamics are present in the Netherlands. This is in line with evidence found previously by Deelen et al. (2018), who find little aggregate labour income share decline, and van Heuvelen et al. (2019) who find an only minimal increase in aggregate mark-ups in the Netherlands. These findings are however at odds with those for the United States, as well as for most other countries explored by Autor et al. (2019). They state that most of the international evidence is in favour of the superstar hypothesis. Unfortunately, their regression does not include the Netherlands so a direct comparison is not possible.

2.3.1 Industry Heterogeneity

The analysis above shows that even though there appear to be firms with superstar characteristics, there is no discernible aggregate superstar dynamic. That is to say, on average, across all Dutch industries, more productive firms do not appear to be more likely to grow their market share than other firms. This absence of superstar dynamics is in line with the fact that the country-level labour income share has remained stable during the period we investigate. How-

Figure 2.2: Logit Coefficient Estimates and Superstar Dynamics Group



Note: The figure shows the resulting coefficients from estimating (2.5) for each industry. Industries are sorted by coefficient size within groups.

ever, it is not in line with the industry-level variation in the labour income share (see figure 2.1). Therefore, we explore the relation between firm productivity and their market share growth, for each industry individually.

To investigate this, we repeat the logit regression in equation (2.5) for each industry. The resulting coefficients (β_1^x) for each industry x, and other regression details are listed in table 2.4 in the appendix. Figure 2.2 lists the results graphically. Eleven out of our 53 industries have positive regression coefficients, whereas the rest are negative. A positive coefficient indicates that productive firms are more likely to gain market share, which is in line with the superstar mechanism. The coefficients for other industries are close to zero or even negative, indicating that productive firms are not more, or even less likely to attain larger market share.

This result and those presented above indicate that some industries feature firms with superstar characteristics *and* dynamics. These industries appear to have a different environment, which is conducive to superstar dynamics. As a natural cut-off point, we split industries into two groups according to their β_1^x estimates. We call the industries with positive estimates 'industries with superstar dynamics', and those that do not as 'other industries'.

To ensure that the cut-off is robust, we repeat the analysis with an alternative specification of TFP, which allows us to use the full 2001-2015 dataset[22]. We only consider industries in the former group if the estimated β_1^x is positive in *both* estimations. This yields a final

[22]For the details of this alternative specification see the descriptions of the robustness analyses in the next section.

group containing ten industries with superstar dynamics, as indicated in figure 2.2.[23]. The ten industries that match the superstar dynamics are listed in table 2.5 are, amongst others, air transport, wholesale, pharmaceuticals, and travels agencies and related activities.

We reiterate the aggregate results presented above, but now we use the industry split to compare the superstar characteristics and dynamics between the two groups. Our previous analysis has already indicated that industries in the superstar group are likely to feature a much stronger relation between firm productivity and the likelihood of increasing market share. We first return to the logit estimate of prediction (4), but estimate it separately for the two subsamples of firms; those in industries with superstar dynamics, and in other industries. The results are shown in the first two columns of table 2.2. There is a rather large difference between the coefficients for firms in the industries with superstar dynamics (positive), versus firms in the other industries (negative). Notably, the coefficients for both groups are highly significant, which is encouraging, given estimates of the individual industries tend to be less precise (see appendix table 2.4).

[23]The results presented in this section, and throughout the chapter are robust to including these industries to the superstar dynamics group.

Table 2.2: Regression results

VARIABLES	(1) Superstar dynamics Logit- Pr(Δvash>0)	(2) Others Logit- Pr(Δvash>0)	(3) Superstar dynamics Mark-Up (Initial)	(4) Others Mark-Up (Initial)	(5) Superstar dynamics Value added Market Shares (Initial)	(6) Others Value added Market Shares (Initial)	(7) Superstar dynamics Labour Share (Initial)	(8) Others Labour Share (Initial)
TFP (initial)	1.448***	−0.809***	1.276***	0.525***	0.140***	0.0681***	−0.345***	−0.127***
	(0.506)	(0.0936)	(0.154)	(0.0456)	(0.0386)	(0.00630)	(0.0536)	(0.00949)
Constant	−1.957***	0.556***	0.404***	0.884***	−0.00837	−0.0923***	0.914***	0.740***
	(0.660)	(0.150)	(0.112)	(0.0716)	(0.0314)	(0.00877)	(0.0548)	(0.0156)
Observations	60,070	182,242	60,070	182,242	60,070	182,242	60,070	182,242
R-squared			0.281	0.086	0.757	0.567	0.285	0.259
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: The table shows the regression results from estimations using equations (2.5) and (2.4), each firm observation is weighted by the average value added market share over its lifetime.

In addition to this clear difference in terms of relation between productivity and the market share growth, table 2.2 also shows the results for testing predictions *(1)-(3)*, in the two industry groups separately. Recall that the superstar hypothesis posits that productive firms have higher market shares *(1)*, higher mark-ups *(2)*, and lower labour income shares *(3)*. We already found these relations in the data by pooling all firms together. However, here we see that all these relations are much stronger in industries with superstar dynamics, though the results are not quite as dramatic as the difference in the estimated relations between productivity and market share. Particularly, note that the coefficient relating productivity to mark-ups is over twice as large for industries with superstar dynamics. Similar patterns hold for the other relations too. These results indicate that not just are the dynamics different between the industries, the two groups also differ significantly in terms of superstar firm characteristics.

Industries in the superstar dynamics group are different from the others as they feature the characteristics and dynamics of superstar firms, as outlined above. Next, we analyse the characteristics of these industries and check whether the outcomes predicted the superstar mechanism, briefly outlined above, are also present in this group of industries in the Netherlands.

2.4 Industries with Superstar Dynamics

In the previous section, we showed that several industries feature the presence of superstar firms and the dynamics associated with the superstar mechanism, while most of the industries do not. This section further explores the characteristics of the group of industries with superstar dynamics and compares them with the other industries. Perhaps other superstar characteristics might be present also, while absent in the other industries.

Autor et al. (2019) posit that due to reallocation of market share towards superstar firms, average productivity would grow, and similarly, that mark-ups would grow, and that the labour income share would decline. This directly follows from the previous predictions where more superstar firms with high productivity, high mark-up, and low labour income shares, gain market share. Given these predictions, and the results of the previous section, we have a further three expectations with regards to the industry outcomes of the superstar mechanism.

Specifically, we expect that through market share reallocation, compared to other industries, *(5) industries with superstar dynamics featured faster average TFP growth*. Similarly, due to reallocation, we expect that *(6) industries with superstar dynamics featured faster average mark-up growth* compared to other industries. And finally, we expect a similar relation for the labour income share; *(7) labour income shares decline (faster) in industries with superstar dynamics*.

First, we examine statistics illustrating the differences between the two groups of industries. Table 2.3 shows the differences between the industry groups in terms of various characteristics. The superstar group is smaller, featuring only about a third of all firms and a quarter of value added in 2006. Average firm sizes in terms of value added are comparable between the groups, and average labour income shares are also similar.

The next columns of table 2.3 show both weighted and unweighted statistics. For the former, firms are weighted by their industry value added share and therefore, each industry retains equal weight, and large firms in one industry are comparable to those in another. The unweighted

Table 2.3: Descriptives main variables - Industry Groups

	Superstar dynamics - vash weighted	Others - vash weighted	Superstar dynamics - unweighted	Others - Unweighted
# Industries	10	43	10	43
	2006	2006		
# Firms	30223	77169		
% of VA	26%	74%		
Av. firm VA	1590	1807		
Av. Labour share	0.645	0.648	0.741	0.762
Av. Mark-up	1.236	1.512	1.393	1.679
Av. Capital intensity	1.727	3.924	1.725	1.910
% - changes		2006-2015		
Δ Labour share	-12%	4%	-2%	-1%
Δ Mark-up	7%	-7%	4%	0%
Δ ln(TFP)	42%	4%	5%	6%
Δ Capital intensity	86%	-2%	19%	13%

Note: The table shows value added share weighted and unweighted averages and percentage changes across the industries in each group. The table shows several variables for the year 2006, along with the total percentage change to labour income shares, TFP, mark-ups, and capital intensity. The latter is defined as the value of the capital stock, divided by the wage bill. Note that these changes are the *percentage change of the (un)weighted average* (not the (un)weighted average of the percentage changes). Figure 2.5 provides a list of industries in each group.

versions of the same statistics are simply the unweighted average of all firms in all the industries in that particular group. Note that both groups have similar average labour income shares in 2006 and industries with superstar dynamics appear to be less capital intensive[24] and have somewhat lower mark-ups, both in weighted and unweighted terms.

The table continues to show the percentage changes of the same indicators for the 2006-2015 period. The labour income share declines faster in industries with superstar dynamics, particularly among higher market share firms, as illustrated by the difference between the weighted and unweighted figures. The reverse appears to be true for the other industries, where the weighted change is positive. TFP growth, and growth of capital intensity, and mark-ups all appear much stronger in industries with superstar dynamics. Again, these developments seem particularly driven by the largest firms, very much in line with the superstar mechanism.

These statistics support all three of the expected outcomes with regards to productivity, mark-ups and labour income shares. However, a final dynamic of the mechanism is not yet confirmed from table 2.3. In particular, predictions *(5)-(7)* state that the reallocation of firm market share plays an important part in the differences between the groups. The next section zooms in on prediction *(7)*, declining labour income shares in industries due to market share reallocation toward superstar firms. We put this prediction under extra scrutiny using a decomposition, examining whether indeed reallocation of market share is part of the mechanism and whether it is more relevant for the industries with superstar dynamics.

2.4.1 Labour Income Share Dynamics

Above we have shown that labour income shares of industries with superstar dynamics tend to decline (faster) and that large productive firms tend to have lower labour income shares. However, while this is in line with the prediction *(7)*, the prediction is more specific. The labour income share is expected to decline due to market share reallocation away from high labour, towards low labour income share firms. Table 2.3 gives some support for this prediction by revealing that the decline of the weighted labour income share is much stronger than the unweighted one in industries with superstar dynamics. Yet this is not enough, as dynamics other than the ones predicted could cause this.

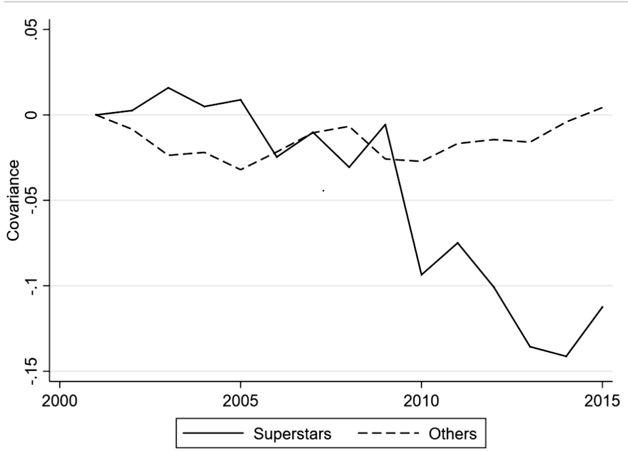
To explore prediction *(7)* further, we evaluate the industry labour income share dynamics using the Olley and Pakes (1996) decomposition. The decomposition is shown in equation 2.6, and splits the labour income share into two terms[25]. The labour income share of an industry x at time t, S_{xt}, is split into an unweighted average $\bar{S_{xt}}$, and the covariance between the labour income share and value added market share (indicated by ω).

$$S_{xt} = \bar{S_{xt}} + (\sum(\omega_{it} - \bar{\omega_{xt}})(S_{it} - \bar{S_{xt}})) \tag{2.6}$$

[24]Possibly because industries with superstar dynamics are disproportionally in services

[25]This decomposition was originally designed for decomposing changes in firm-level productivity, yet works for the labour income share too (Autor et al., 2019). A dynamic version of this decomposition including the contributions of entry and exit, following Melitz and Polanec (2015) exists. The appendix shows the results of a similar exercise using this dynamic decomposition approach (figures 2.7-2.6). These alternatives suggest that besides reallocation among surviving firms, entry- and exit-dynamics also differ strongly between superstar and other industries.

Figure 2.3: Development of decomposition covariance term, 2001-2015.



Note: This figure shows the covariance term of industry-level OP decompositions. Each line shows the unweighted averages of the industry level covariance terms for the industries with superstar dynamics or other industries.

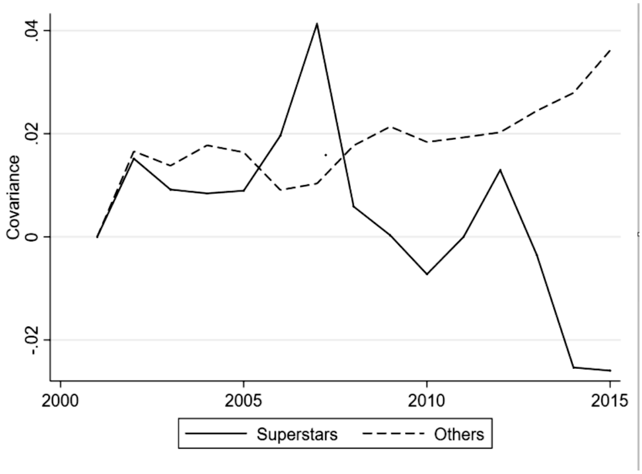
The covariance term indicates if there is a systematic relation between value added market share and labour income shares. For example, a negative covariance term could indicate that relatively large firms tend to have lower than average labour income shares. Figure 2.3 splits industries into superstars and others and shows the development of the covariance term for both groups. By examining the covariance terms, we might gain some insight into how labour income shares develop across these different industry groups. The result shows that the covariance term for the superstar dynamics group shows a decidedly different pattern from the other industries, particularly after 2008 when it declines much stronger.

The different pattern for the two industry groups can be interpreted in multiple ways. Either value added is being redistributed towards large low labour income share firms, or the largest firms have reduced their labour income shares, without much value added share changes. Alternatively, additional small firms might have entered the market, with higher than average labour income shares. This would inflate the unweighted average (RHS term 1 in equation (2.6)) and make the covariance term turn negative. This final explanation we can discard, as we do not see the unweighted average labour income share increase systematically in either group[26]. However, with the current results, we cannot conclusively distinguish between the first two explanations. To be able to do this, we perform another decomposition, this time keeping each firm's labour income shares constant (at their initial value). If we see that the covariance decline in the superstar group now disappears, the labour income share decline is due to declining labour income shares within firms. However, if the declining covariance is maintained, value added reallocation is the relevant driver of declining labour income shares[27].

[26]See appendix table 2.6.

[27]The equation used for the counterfactual decomposition is the same as equation (2.6), except for the fact that the labour income share always stays at time 1 for the firm. $S^*_{xt} = \bar{S_{xt}} + (\sum(\omega_{it} - \bar{\omega_{xt}})(S_{1t} - \bar{S_{1t}}))$, where

Figure 2.4: Development of decomposition covariance term, 2001-2015; counterfactual



Note: This figure shows the covariance term of a counterfactual OP decomposition. The labour income share of each firm is held constant throughout their lifetime for this decomposition. Each line shows the unweighted averages of the industry level covariance terms for the industries with superstar dynamics or other industries.

Figure 2.4 shows that when each firm's labour income share is held constant, the negative trend for the superstar group persists, though it is less pronounced before 2008. However, the difference in covariance term developments between superstar and other industries remains clear. This indicates that the decreasing covariance term of these industries is most likely due to low-labour income share firms having expanded their value added market share[28].

This result is in line with prediction *(7)*, the most important prediction for our purposes. In industries with superstar dynamics, labour income shares are lowered due to market share reallocation induced by superstar dynamics. This negative labour income share trend, like the superstar dynamic, is absent from the other industries. Next, we present some robustness test for our results, we discuss the results and conclude in a final section after that.

2.4.2 Robustness

We have performed several robustness checks to evaluate the stability of the results presented above. First, the data contains many very small firms, which might affect the relationship we find. In the main analysis, we removed the very smallest first, those with one FTE's or less. To check for the relevance of this, we remove all firms that have less than ten FTE's instead. Doing so does not affect the results substantially. The composition shows patterns that are

S_{1t} refers to the initial value of a firms labour income share when it enters the sample.

[28]This observation is in contrast with evidence on Dutch firms presented in Deelen et al. (2018). Differences in data and methods can explain these disparate findings. First, they use a shift-share decomposition which puts additional weight on larger firms, this might lead to a different within-, and by extension reallocation terms, compared to the MP methodology. Secondly, they group firms in percentiles, which might understate the reallocation term for small reallocation effects within these percentile groups. Third, they use different, survey-based, data that contains less detail for smaller firms.

highly similar to the ones presented above. For the regressions, the signs, significance, and size of coefficients are similar, and all conclusions are the same.

The second check we perform is to choose a different outlier strategy. The main analysis has winsorised firm-level TFP and mark-up outliers at below the 3^{rd} and above the 97^{th} percentiles. Here we check how the results hold up against applying more stringent outlier removal strategies. Our alternative is to winsorise at the bottom and top 5^{th} percentiles. Using this alternative outlier strategy, the regressions stay virtually unchanged.

In the third and final robustness check we change the periods we consider. The main regression analysis examines the period 2006-2015, even though some of our data is available starting in 2001. To start our analysis in 2001, we need to change several variables in our production function. Specifically, to estimate our gross output production function, we change the labour input from labour hours to labour costs; additionally, we can no longer use wages as an instrument variable. Some studies, most notably Gandhi et al. (2017), advise against such changes. And indeed, the estimation using labour costs yields strange results: negative capital coefficients and TFP estimates are altered significantly. The correlation between our preferred method's TFP estimates and the labour-cost ones is only around 0.5, the correlation between the changes in the TFP measures is even lower.

If we push on regardless, our final results are only slightly altered. In general, the sizes and significance of the coefficients are comparable. If anything, our results are stronger by using the 2001-2015 period. The superstar dynamics that we uncovered also appear when we use this alternative specification. This is an indication that our findings are not purely the result of our choice for the 2006-2015 period. Note that when we use the full 2001-2015 sample, the ranking of industries by the TFP-growth coefficients changes. Firstly, there are more industries for which we estimate positive TFP-growth coefficients; secondly, the set of industries is somewhat different. These differences are mostly due to the altered TFP estimates, rather than the extra years.

2.4.3 Summing Up

The results of the analyses have shown that in some industries superstar dynamics are present, while not in others. In the industries with superstar dynamics, productive and low labour income share firms have attained market power, and are more likely to increase their market share further. By doing so, these firms suppress the aggregate labour income share of their industry. This is demonstrated by the decomposition results that reveal significant reallocation dynamics driving labour income shares down in the industries with superstar dynamics.

Our results complement the current literature, by linking the superstar mechanism to specific industries, rather than the whole economy. However, we do not explicitly uncover how it is that these industries are different. A thorough exploration of this is beyond the scope of this chapter . However, turning back to table 2.3, and the discussion about the industry groups above, several factors could be responsible for making industry environments conducive to superstar dynamics. We leave the detailed empirical exploration to future work, but in the next section discuss some of the factors that could contribute to establishing the industry environments conducive to superstar dynamics.

2.5 Intangibles, Technology, and Globalisation

In this section, we discuss other developments that might have contributed to some industries developing superstar dynamics. While this might not present conclusive answers, it does suggest as to what the relevant factors might be and suggests ways forward for future inquiries. Recall the example of the travel agency industry, discussed in the introductory chapter of this dissertation. This is a good illustration of an industry with superstar dynamics driven by several platform-based superstar firms[29].

More generally, various industry characteristics might contribute to superstar dynamics. One of the strongest contrasts from table 2.3 is that the average capital intensity growth is higher in industries with superstar dynamics than in the other industries. Unfortunately, the microdata does not allow us to explore the specific assets of firms' capital stocks in more detail. However, industries in which specific types of capital are more profitable might be those where superstar dynamics flourish. For example, superstar firms might be more intensively using intangible capital, like organisational capital, software, and R&D. Intangible assets are often highly firm-specific, and scalable at very little marginal cost once developed (Haskel and Westlake, 2017). As such, industries in which intangibles can be productively used could be extra conducive to the establishment of large and productive superstar firms. Similar arguments can be made for ICT or automation capital. Each of these might enhance firm productivity and allow rapid growth.

This is particularly related to De Ridder (2019), who develops a model of productivity and competition, specifically modelling the adoption of intangible assets. He concludes that when firms successfully employ intangible capital assets on a large scale, economic activity concentrates around these intangible intensive firms. Due to intangibles, the productivity of these firms is/can appear much higher than other firms, and they are likely to be larger firms. These intangible intensive firms fit the 'superstar' bill nicely. Unfortunately, the data available on intangible capital does not allow for a sufficiently detailed examination of these characteristics and their role in superstar dynamics.

Another important industry environment factor might be internationalisation or foreign ownership of firms. Particularly, the Netherlands is a small economy, and though relatively wealthy, the market is small compared to other, larger advanced economies. It would seem that firms in the Netherlands must look abroad to attain the growth, and the scale required to become a superstar firm. This can be a difficult process, potentially made easier by foreign ties and investors. Foreign expertise, money, and market access might significantly increase the odds of superstar dynamics being established in an industry. Alternatively, industries that are relatively 'footloose' might have an advantage in such cases. Industries in which firms primarily use the internet to conduct business are the most obvious example of such industries; like the travel agency platform firms discussed in the introduction.

Finally, combining the arguments above, some authors have linked the developments of globalisation and rising use of intangible assets in production. See Chen et al. (2017) for how international production fragmentation, offshoring, and intangible capital might be related. The next chapter of this thesis continues along this train of thought and relates globalisation

[29] See Cennamo and Santalo (2013); Economist (2005) for more on the platform economy.

to changes in the residual income share, a large part of which is income generated by using intangibles.

2.6 Conclusion

In this chapter we explored the dynamics affecting industry labour income shares in the Netherlands using restricted-access microdata on non-financial corporations for the period 2001 to 2015. Our first contribution has been to highlight the finding that despite an aggregate labour income share trend that has stabilised in recent years, the underlying dynamics have still seen significant changes. Particularly, our results revealed that the labour income share increases in some, but declines in other industries. We continued by linking these labour income share changes to superstar dynamics, whereby productive low labour income share firms increasingly attain market share. Indeed, we find that market share reallocation exerted significant downward pressure on the labour income share in some industries. In these industries, the superstar firms can increase market power and dominance. In the industries without superstar dynamics, productive firms seemingly fail to translate their productivity advantage into market share growth, leaving industry labour income shares stable or even increasing.

This is evidence that the superstar mechanism is less relevant for the Netherlands than in the United States, where, it is argued by Autor et al. (2019), it is an important driver of declining aggregate labour income shares. Our finding lines up with other evidence that goes against an aggregate superstar mechanism in Europe and the Netherlands specifically (Döttling et al., 2017; Guschanski and Onaran, 2018; van Heuvelen et al., 2018, 2019). The Netherlands is not included in the international firm-level analyses of Autor et al. (2019), so a direct comparison is impossible. However, their industry-level analyses show that industry labour income share changes in the Netherlands appear to vary quite strongly from other OECD countries; the correlation between Dutch industry labour income share changes and those in other OECD countries is quite low, never above 0.3. These findings combined with our own, and the fact that we see much heterogeneity in terms of labour income share developments across industries, suggests industry superstar dynamics might differ by country. If indeed the superstar mechanism is responsible for industry labour income share declines, but the superstar dynamics differ by country, we might see very different aggregate labour income share change outcomes. This idea corresponds to Cette et al. (2019), who find that aggregate labour income share declines are not homogenous across countries.

Other developments might contribute to establishing the environments conducive to superstar dynamics. These factors include the share of foreign ownership, allowing firms easier access to foreign finance, and markets. Increasing international integration of production processes and other issues related to globalisation could be significant contributors to superstar dynamics, allowing firms to grow larger, and less dependent on and constrained by their home countries. Other factors that might contribute are new technologies like ICT, or intangible capital production factors like organisational capital and R&D.

Lastly, several caveats are in order. Firstly, the microdata allows us to explore firm-level dynamics in great details, yet the downside is the limited time-span which includes some data breaks. While the main dataset goes back to 2001, we are only able to estimate the production function with some level of confidence after 2006, when all the necessary data are available. Estimations for the period 2001-2006 require us to make additional assumptions that are more contested in the literature. This is borne out by the relative sensitivity of some of our estimates to using different production specifications and definitions of the inputs. Secondly, our estimations of TFP and mark-ups are mechanically related through the estimation methods, though the concepts aim to capture differ concepts. While we do not observe problems with collinearity or related issues in our analyses specifically, we cannot guarantee their total absence. Finally, our analyses do not allow us to say much about causality in the relations we have shown. For example, unobserved factors may be driving both firm market share growth and firm productivity. While we observe that in some industries more productive firms are also more likely to increase their market share, we cannot state that these firms are more likely to gain market share *because* they are more productive.

Appendix

2.A Appendix Figures & Tables

Table 2.4: Individual Industry market share - TFP regression coefficients

Industry (sbi 2008)	TFP (initial)	Stnd. Err.	Constant	Observations
1	−1.591***	(0.229)	1.614***	6,446
10	−3.410***	(0.795)	1.708***	1,894
13	−1.134**	(0.496)	−0.692***	449
14	−0.756	(0.830)	0.707	247
15	0.992	(3.221)	−1.628	124
16	−0.0927	(0.632)	−0.366	817
17	−0.708	(0.926)	−0.987***	334
18	0.0606	(1.044)	−0.170	1,885
20	−1.047**	(0.497)	1.140**	614
21	2.794***	(0.778)	−2.158***	143
22	−0.292	(0.624)	−0.611	976
23	−0.594	(0.528)	0.204	706
24	−4.348***	(1.453)	2.759**	253
25	−0.986*	(0.579)	0.285	4,422
26	0.857	(1.702)	−2.145***	718
27	−9.249*	(4.768)	8.953*	599
28	1.977	(1.915)	−0.460	2,103
29	−7.231***	(1.311)	3.836***	466
30	−5.212*	(2.968)	3.608*	563
31	−1.861***	(0.674)	0.501*	1,189
32	−1.514**	(0.594)	−0.266*	1,199
33	−1.571***	(0.380)	−0.463***	1,913
41	−2.220***	(0.542)	1.155***	8,060
42	−0.680	(1.709)	−0.207	1,720
43	−0.577	(0.433)	0.212***	13,453
45	1.696	(1.119)	−0.520	7,920
46	0.0191	(0.380)	0.630	35,457
47	−1.541*	(0.806)	0.456	17,190
49	−1.052**	(0.448)	0.283**	5,348
50	−0.614***	(0.197)	0.246	1,031
51	1.388	(1.198)	0.741	98
52	−0.779*	(0.433)	0.461	2,812
53	−5.385	(5.191)	4.450	453
55	−1.005***	(0.254)	0.515	2,008
56	−0.195	(0.233)	−0.535***	7,269
58	−1.927***	(0.724)	0.845**	1,146
59	−0.594	(0.597)	0.445	1,526
61	−1.155	(1.243)	0.755	525
62	−0.340	(0.275)	−0.121	13,177
63	−1.893***	(0.469)	0.230	1,309
69	−0.962***	(0.217)	2.246***	15,586
70	−0.847***	(0.119)	1.005***	41,618
71	0.443	(0.682)	−0.448**	10,594
72	−0.882	(0.909)	0.0439	996
73	−0.619*	(0.345)	−0.0971	5,774
74	−0.556	(0.419)	−0.0680	3,503
75	−0.798	(1.308)	−0.510	355
77	−0.151	(0.437)	−1.086*	1,879
78	−0.275	(0.260)	0.767*	7,710
79	6.750***	(2.375)	−6.117***	1,028
80	−1.557***	(0.378)	−1.516***	793
81	0.00981	(1.154)	−0.412***	2,531
82	−1.220**	(0.547)	0.580	1,383

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.5: Industries with Superstar dynamics and Others.

SBI / ISIC rev. 4	Superstar
15	Manufacture of leather and related products
18	Printing and reproduction of recorded media
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
26	Manufacture of computer, electronic and optical products
28	Manufacture of machinery and equipment n.e.c.
45	Wholesale and retail trade and repair of motor vehicles and motorcycles
46	Wholesale trade, except of motor vehicles and motorcycles
51	Air transport
71	Architectural and engineering activities; technical testing and analysis
79	Travel agency, tour operator and other reservation service and related activities
	Others
1	Crop and animal production, hunting and related service activities
10	Manufacture of food products
13	Manufacture of textiles
14	Manufacture of wearing apparel
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
17	Manufacture of paper and paper products
20	Manufacture of chemicals and chemical products
22	Manufacture of rubber and plastic products
23	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment
27	Manufacture of electrical equipment
29	Manufacture of motor vehicles, trailers and semi-trailers
30	Manufacture of other transport equipment
31	Manufacture of furniture
32	Other manufacturing
33	Repair and installation of machinery and equipment
41	Construction of buildings
42	Civil engineering
43	Specialised construction activities
47	Retail trade, except of motor vehicles and motorcycles
49	Land transport and transport via pipelines
50	Water transport
52	Warehousing and support activities for transportation
53	Postal and courier activities
55	Accommodation
56	Food and beverage service activities
58	Publishing activities
59	Motion picture, video and television programme production, sound recording and music publishing activities
61	Telecommunications
62	Computer programming, consultancy and related activities
63	Information service activities
69	Legal and accounting activities
70	Activities of head offices; management consultancy activities
72	Scientific research and development
73	Advertising and market research
74	Other professional, scientific and technical activities
75	Veterinary activities
77	Rental and leasing activities
78	Employment activities
80	Security and investigation activities
81	Services to buildings and landscape activities
82	Office administrative, office support and other business support activities

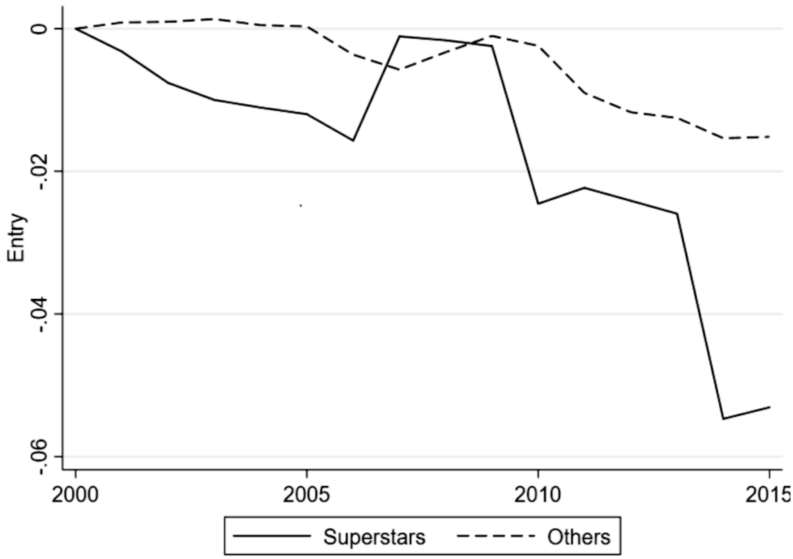
Note: The table list industries in the superstar dynamics group and others

Table 2.6: Olley and Pakes (1996) Decomposition values

	actual				counterfactual			
	Superstars		Others		Superstars		Others	
year	Covariance	Mean Labour Share	Covariance	Mean Labour Share	Covariance	Mean Labour Share	Covariance	Mean Labour Share
2001	-0.085	0.764	-0.075	0.752	-0.085	0.764	-0.075	0.752
2002	-0.093	0.788	-0.081	0.776	-0.070	0.769	-0.058	0.746
2003	-0.077	0.796	-0.099	0.793	-0.076	0.765	-0.061	0.748
2004	-0.088	0.778	-0.096	0.777	-0.077	0.779	-0.057	0.745
2005	-0.078	0.761	-0.108	0.768	-0.076	0.770	-0.058	0.744
2006	-0.109	0.749	-0.097	0.744	-0.066	0.754	-0.066	0.741
2007	-0.089	0.737	-0.087	0.724	-0.044	0.743	-0.065	0.736
2008	-0.112	0.782	-0.081	0.740	-0.079	0.740	-0.057	0.734
2009	-0.103	0.824	-0.099	0.801	-0.085	0.738	-0.053	0.732
2010	-0.156	0.819	-0.104	0.790	-0.093	0.747	-0.056	0.739
2011	-0.168	0.784	-0.087	0.777	-0.085	0.733	-0.056	0.736
2012	-0.178	0.809	-0.087	0.799	-0.072	0.735	-0.055	0.734
2013	-0.188	0.810	-0.093	0.796	-0.089	0.736	-0.050	0.729
2014	-0.210	0.773	-0.076	0.764	-0.111	0.735	-0.047	0.725
2015	-0.186	0.754	-0.068	0.742	-0.111	0.737	-0.039	0.721

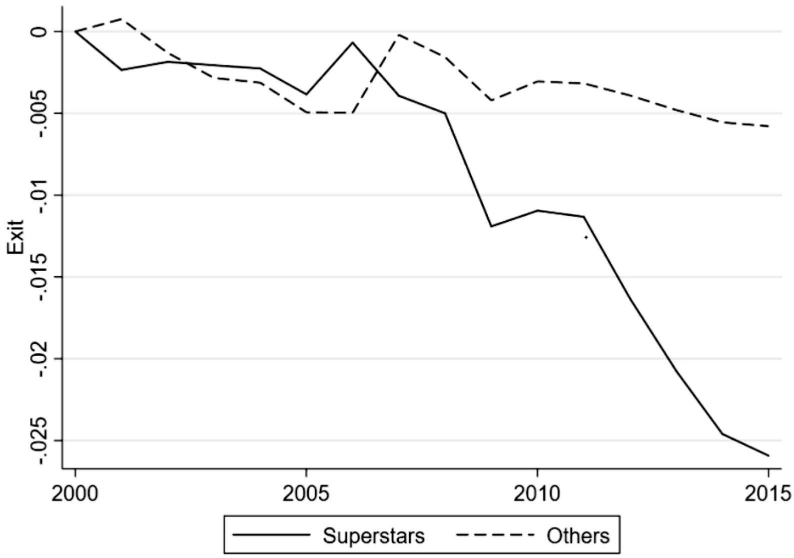
Note: The underlying numbers of figures 2.3 and 2.4

Figure 2.5: Cumulative Covariance of *entering firms* based on a Dynamic Olley and Pakes (1996) Decomposition



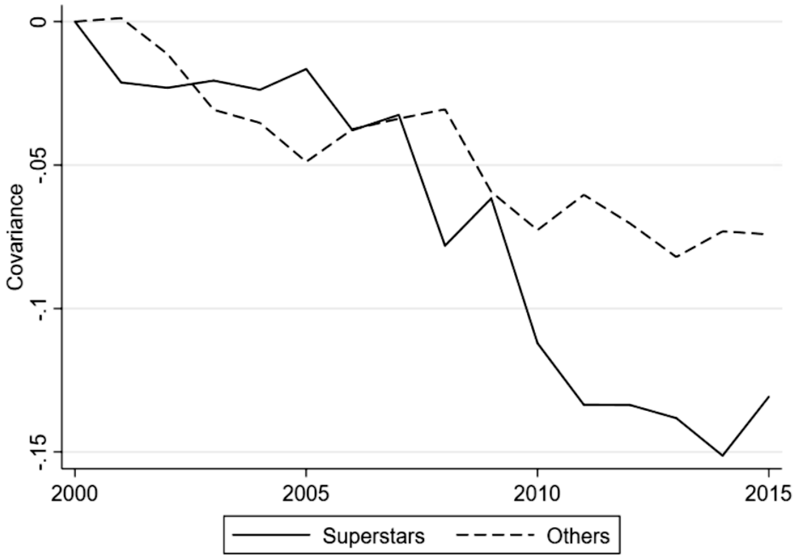
Note: This decomposition uses the Dynamic Olley Pakes decomposition due to Melitz and Polanec (2015)

Figure 2.6: Cumulative Covariance of *exiting firms* based on a Dynamic Olley and Pakes (1996) Decomposition



Note: This decomposition uses the Dynamic Olley Pakes decomposition due to Melitz and Polanec (2015)

Figure 2.7: Cumulative Covariance of *Surviving firms* based on a Dynamic Olley and Pakes (1996) Decomposition



Note: This decomposition uses the Dynamic Olley Pakes decomposition due to Melitz and Polanec (2015)

2.B Data-selection

Enterprises are dropped if no industry identifier is assigned for its entire life-span. Overall, for the final dataset, we make some adjustments to assure data quality. As in Autor et al. (2019) we use only “Employer firms”, and drop firms if they have no employees (i.e. less than one FTE). Furthermore, several steps of cleaning have been performed on the data: we drop observations if labour income is missing at the start or end of an enterprise’s appearance in the data. Observations are also dropped if labour income is negative. Observations are dropped if sales are negative. Firm-year labour share observations are winsorised at the 95^{th} percentile of their respective industry. Enterprises are dropped if more than 50% of their labour share observations are below zero or above one. Mark-up and TFP observations are winsorised at the 3^{rd} and 97^{th} percentiles of their industry-year. This is to deal with extreme outliers of TFP and mark-ups. This way, the maximum value as mark-up at the firm level is about 17 (times marginal cost), and (log) TFP is just over 4.

To estimate productivity, we drop the following industries/sectors because they are not conducive to the estimation of the production function D, E, K, L, O, P, Q, R, S, T, U, as well as the more detailed industries: 02, 03, 11, 12, 60. Some of these could be included for labour share calculations, but to retain a coherent industry coverage, they have not been included in the main body of this chapter. For the aggregate trends, the individual inclusion or exclusion of the larger sectors (primarily D, E, K, L, O) have some level-effects, but trends remain very similar. The smaller sectors and industries have little impact on aggregate levels and trends. The final set of industries covers 53 industries at the 2-digit SBI level.

The dataset that we use is based on the NFO (non-financial organisations) dataset produced by statistics Netherlands. While this data is very comprehensive and includes more or less all non-financial corporations in the Netherlands for 2001-2015, some issues persist. Specifically, due to a change in the source material for the dataset, firm identifiers are altered between 2005 and 2006. This leads to many firms being ’discontinued’ in 2005, and ’started up again’ in 2006 under a different identification number. For this reason, throughout the analysis, we avoid using the 2005 to 2006 difference when firm-level data is involved.

2.C Mark-up Estimation

For a given production function:

$$Q_{it} = A_{it} K_{it}^{\beta^K} L_{it}^{\beta^L} M_{it}^{\beta^M} \tag{2.7}$$

The first order condition for the variable input M_{it} is:

$$\frac{\partial \mathcal{L}_{it}}{\partial M_{it}} = P_{it}^M - \lambda_{it} \frac{\partial Q_{it}}{\partial M_{it}} = 0 \tag{2.8}$$

where $\mathcal{L}_{it}$ is the Lagrangian assuming producing firm i is cost minimising at time t. P_{it}^M is the firm’s input price for variable input M_{it}. Finally, λ_{it} is marginal cost of production.

Rearranging equation (2.8) and defining mark-ups (μ) as the output price (P^Q) over marginal costs, we can define mark-ups as:

$$\mu_{it} = \beta_{ct}^{M} * \frac{P_{it}^{Q} Q_{it}}{P_{it}^{M} M_{it}} \tag{2.9}$$

For additional details on the methodology of the mark-up estimation we refer the reader to Hall (1988), De Loecker and Warzynski (2012), and van Heuvelen et al. (2018).

Chapter 3

Factorless Income in a Globalising World: Measurement and Analysis

3.1 Introduction

Labour's share in GDP is on the decline across a broad set of countries since the 1980s, and a sizeable literature has emerged aimed at explaining the drivers of the phenomenon (Karabarbounis and Neiman, 2014; Elsby et al., 2013; Grossman et al., 2017). However, it is becoming increasingly clear that the labour share decline cannot be accounted for by an offsetting increase in the share of capital income (Karabarbounis and Neiman, 2018; Barkai, 2016). In fact, the share of GDP unaccounted for by labour or capital has been increasing in recent decades. Since this income is not accounted for by labour or capital, Karabarbounis and Neiman (2018) call it the 'factorless income share'. They show its evolution for the United States since the 1960s, revealing that the factorless share has varied a great deal over time but has been on an increasing trend since the 1980s.

To illustrate, equation 3.1 shows GDP consists of income flows generated by employing the tangible capital stock and labour, tangible capital income (rK) and labour income (wL): each factor generates a share of income. The third term (F) is factorless income, which consists of income that is not accounted for by labour or tangible capital[1]. In this chapter, I estimate and explore this factorless income share across a set of developed countries.

$$GDP = rK + wL + F \tag{3.1}$$

Interpreting factorless income and its dynamics is an important issue with significant implications. It is important because we cannot account for factorless income; in addition, we also lack understanding about where, or to whom this factorless income accrues. Knowing how to account for factorless income improves our understanding of changing production structures in an increasingly globalising economy. Furthermore, a growing factorless share might imply a changing income distribution. Different drivers might lead to increasing factorless income shares, with rather different implications. These drivers include significantly higher economic firm profits, or rising perceived risk of investments in capital, as I will explain below. The interpretation of factorless income is also important for policy-makers, to know if, and which policies should be enacted.

This research aims to evaluate our ability to account for the factorless income share. To do so, I start by estimating the income shares of labour and tangible capital. Using data from the EUKLEMS database, I derive factor income shares for a set of advanced European economies

[1] Or at least measured capital, there might be un- or mismeasured tangible capital types that account for this part of income, as elaborated on below, and in Karabarbounis and Neiman (2018).

and the United States, across a number of industries that cover the market economy. Figure 3.1 shows the income share trend across countries and industries for each factor since the mid-1980s. It is clear from the figure that income shares of labour and tangible capital have declined in the developed world. This has been paired with a significant rise of the factorless share, especially during the late 1990s.

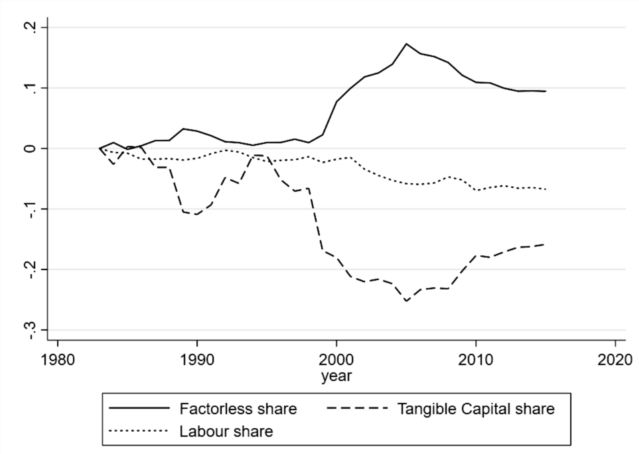
In the effort to account for the dynamics of factorless income, the first step is to evaluate the assumptions made when computing the labour and tangible capital shares. One contentious issue for the estimation of these shares is the assumption made about the income of self-employed persons. I discuss this issue and demonstrate that it is relevant for the labour share trend across the ten countries. Another important assumption is the expected rate of return on investments of tangible capital assets. This rate of return is at the heart of estimating the tangible capital income share, and it reflects the perceived risk of the investments. The first contribution of this chapter is to evaluate different rates of return, and showing that even taking changing risk patterns into account, a sizeable factorless income share persists across countries. Using the industry-level data, I document that in addition to the aggregate factorless share dynamics, much heterogeneity exists between industries, and across countries. These findings complement and expand on the findings of previous literature, which has mostly focussed on the United States national level (Karabarbounis and Neiman, 2018; Barkai, 2016).

Unable to account for factorless income shares using labour and tangible capital, the next step is to expand the set of factor inputs by including intangible capital inputs (Corrado et al., 2005; Koh et al., 2019). These assets include firms' brands, proprietary designs, and organisational capital, among others. Each of these can be seen as productive assets in production (Corrado et al., 2005). However, these intangible assets are not measured as capital assets in current national account statistics, as opposed to software and R&D, which are. The second contribution of this chapter is to capitalise intangible assets, treating them as tangibles, to account for factorless income dynamics, using the INTAN-invest database (Corrado et al., 2016). I estimate the rate of return that would be required on intangibles to account for all factorless income, but the results far outstrip the rate of return on tangible assets. This result might suggest that the current intangible asset data are not sufficient to account for factorless income.

Given that capitalising intangible assets appears insufficient to account for factorless income, an alternative is to explore the relation between intangibles, and globalisation through international trade. This link is motivated by viewing production through global value chains. Chen et al. (2017) argue that intangible assets are high fixed cost investments, but, once acquired, can be extended geographically at relatively little cost. This means intangible capital is most beneficial to the largest globalised firms, which can spread out the fixed of acquisition the most (Corrado et al., 2016; De Ridder, 2019). Additionally, in an international setting, communication-related intangibles like software and organisational capital might be much more valuable. In addition to this, De Loecker et al. (2016) find that mark-ups of firms increase after trade liberalisations. These increasing mark-ups might indicate firms are investing in more high-fixed costs intangible assets.

If increased trade integration reflects the use of intangibles, it can explain an increase in factorless income too, as long as intangible assets are not (fully) accounted for. The third

Figure 3.1: Factor Income Shares - Trend across countries & industries



Note: The figure shows the year fixed effects of an (value added weighted) income share regression, which includes industry and country fixed effects. The tangible capital share is based on calculations using a WACC rate of return, and the set of tangible assets only (see columns one of appendix table 3.7). Further explanations below.

contribution of this chapter is to explore the relation between factorless income and international trade. Following the hypothesis set out by Chen et al. (2017), I relate the developments of industry factorless shares to international trade. To do so, I use two measures derived from the World Input-Output Database (WIOD), which reflect offshoring and international competition (Timmer et al., 2015). The results of the regressions indicate that trade is significantly related to factorless income. However, the variation explained is relatively modest. Particularly, I find offshoring to be positively related to industry factorless shares, which is in line with Chen et al. (2017). At the same time, higher import competition appears negatively related to the factorless share. This might be an indication that firms in more competitive environments have difficulty mustering the resources to invest in intangibles, and are thereby forced to lower mark-ups.

The chapter is most closely related to the work by Karabarbounis and Neiman (2018), Chen et al. (2017), and Barkai (2016). Karabarbounis and Neiman (2018) present three cases, or narratives to help make sense of the rising factorless income share; rising profits, mismeasured capital, and increasing risk or higher investment return uncertainty. Firstly, rising profits are related to the literature documenting rising mark-ups and profits of firms (Barkai, 2016; Karabarbounis and Neiman, 2014; De Loecker et al., 2018a; Calligaris et al., 2018). The authors suggest that capital holders capture an increasing share of income in the form of higher economic profits. These higher profits are made by some firms with increasing market power, allowing them to charge higher mark-ups. However, this interpretation is contested in the literature; Traina (2018) and Karabarbounis and Neiman (2018) argue that observed increase of mark-ups might be driven by intangible assets. In this narrative, certain developments allow firms to increase their mark-ups through market power over consumers and competitors. Autor et al. (2019) and Kehrig and Vincent (2018) suggest a class of superstar firms is becoming increasingly prominent. These firms are 'hyper-productive' and manage to capture large shares of their markets and increase their economic profits, ultimately raising factorless income. Developments that could have contributed to such superstar firms are increasing use of intangible assets (De Ridder, 2019), ICT (Barkai, 2016; Karabarbounis and Neiman, 2018), or international trade (Melitz, 2003).

The second narrative introduces the role of the missing capital stock, which consists of assets not capitalized in the national accounts. These assets include intangibles like brand value and organisational capital (Corrado et al., 2014; Koh et al., 2019; Chen et al., 2017; Haskel and Westlake, 2017). In addition to intangible capital, other often unmeasured production factors are land and other natural capital types, like forests, and sub-soil assets (Inklaar, 2010; Brandt et al., 2017; Freeman et al., 2020)[2].

These assets could, when capitalised, account for additional income that was previously classified as factorless income. Particularly, assumptions on depreciation, prices, vintages, and others can play an important role in the measurement of capital income (Karabarbounis and Neiman, 2018). Logically, when capital income is mismeasured and underestimated specifically, factorless income might be overestimated because not all factors of production are correctly accounted for. However, only if these issues worsen over time will they contribute to explaining an increasing factorless share. A large literature has found that investments in intangibles have grown significantly in recent decades. (Corrado et al., 2005; Chen, 2017). For this reason, intangible capital is the primary candidate to explain factorless income through this narrative.

The third narrative emphasises the rate of return. It suggests perceived firm opportunity costs might exceed observed safe returns, creating a 'wedge' between the two. A potential explanation is the increasing risk that firms face, pushing them to require higher returns on investments. This wedge can account for factorless income by raising capital income above what would be expected given safe returns (Jordà et al., 2019; Duarte and Rosa, 2015).

Inklaar (2010) finds that the measurement of capital income is rather sensitive to the rate of return assumption, and therefore so is factorless income. The rate of return narrative can only help to account for rising factorless incomes if investments are becoming more risky, or other developments are making the rate of return wedge larger. Particularly, note that investments in some assets might be riskier than others. A shift towards using such assets in production might increase average risk face by firms.

Intangibles are again a good example since these assets have grown as a share of total investments. Hall (2001) and Hansen et al. (2005) suggest risk might be higher for intangible assets requiring higher premiums, and higher resulting returns. Farhi and Gourio (2018) link the rate of return wedge to increasing intangibles, higher risk-premia, and rising market power. Similar findings are documented by Eggertsson et al. (2018), who focus on market power. De Ridder (2019) links the rise of intangibles to several different developments including declining labour shares and increasing mark-ups. This provides a further link between the different cases, suggesting that all are likely relevant and interconnected at the same time.

So far, this type of research has strongly focussed on the United States, yet existing literature

[2]Unfortunately, data constraints do not allow me to add such data. Though most of these appear to account for a relatively small part of GDP, especially in developed economies.

has documented important differences across countries in terms of changes in factor shares (Cette et al., 2019). Similarly, differences in rising profits and adoption of intangibles are documented, specifically between the United States and Europe (Gutiérrez and Philippon, 2017; Döttling et al., 2017; van Heuvelen et al., 2018; Calligaris et al., 2018; McAdam et al., 2019). As such some factors may be more relevant in some countries than others[3]. This further motivates the international viewpoint I use in this chapter .

In the next section, I outline the estimation of the factor income shares. Because of the ambiguity of the term 'factorless', the next sections will be more specific in terminology. For estimation of the labour share, I pay specific attention to the allocation of mixed-income, primarily generated by the self-employed (Krueger, 1999; Gollin, 2002). Subsequently, I outline the estimation of tangible capital income and derive its income share. The rate of return on capital assets is a key aspect of estimating tangible capital income (e.g. Inklaar (2010); Hall and Jorgenson (1967)). Without consensus in the literature about what specific rate of return to use, I outline and apply two different alternatives. Finally, I derive the intangible capital income share defined as the share of income not accruing to labour or tangible income and show its developments over time and across sectors.

The third section outlines the steps necessary to capitalise intangible capital, the capital assets most likely able to account for factorless income. I include the intangible capital input as a factor of production to account for the factorless share. Assuming that labour, tangible capital, and intangible capital exhaustively account for GDP, I derive and examine an ex-post rate of return specific to intangible assets. This is in line with Hansen et al. (2005) who argue that the rate of return on intangibles might very well be different from that of other assets. Despite this, the resulting rates are nowhere near realistic, given rates on tangible capital. Intangibles can account for some of the aggregate growth, but appear insufficient to account for the level and dynamics of factorless income.

In the fourth section, I explore the relation between factorless income and globalisation through trade. This econometric exercise reveals the increasingly international production processes of firms contribute to factorless income dynamics. International trade might constitute an important factor in the developments of factorless income, in particular through its relation with intangibles. In the fifth and final section I discuss the results and their implications, with an additional focus on the potential of using a global value chain (GVC) framework in future factor income research.

3.2 Measurement & Data

The dataset I rely on primarily is the 2017 release of the EUKLEMS dataset (Jäger, 2018). I consider the industries included in the market economy, as identified by Jäger (2018) and used by Autor and Salomons (2018) among others. This dataset contains industry-level data for a set of industries and OECD countries[4]. The data provide the building blocks for the labour share as well as the tangible capital and factorless shares. The latter two additionally require

[3]Or, for that matter, across time and/or industries.

[4]These industries are (ISIC rev. 4): 10-12, 13-15, 16-18, 19, 20-21, 22-23, 24-25, 26-27, 28, 29-30, 31-33, 58-60, 61, 62-63, A, B, D-E, F, G, H, I, K, M-N. They cover the market economy.

some assumptions and extra data.

In addition to the EUKLEMS data, I use data from the World Input-Output Database (WIOD) to derive import competition and offshoring as measures of international trade. I discuss these measures in more detail later. This database is a comprehensive input-output table, which tracks intermediate and final goods within and across borders for a set of countries and industries similar to the KLEMS data. Combining the KLEMS data with the WIOD trade data yields a dataset that runs from 2000 to 2014, contains 10 counties and 23 industries covering the market economy in each country.

Equation (3.1) shows how total value added is made up of three parts: labour, capital, and factorless income. This implies that I estimate factorless income as a residual. It consists of the income that is left over after subtracting labour and capital income from total (industry) value added (Chen, 2017; Karabarbounis and Neiman, 2018). As I compute factorless income as a residual, it is subject to any assumptions made in the calculation of labour and especially capital income. Given these different assumptions, different definitions of factorless income are possible. This section proceeds by describing how labour and capital income are estimated. At I define *intangible* income, which is the income unaccounted for by labour and tangible capital as my first estimate of factorless income.

3.2.1 Labour income

The allocation of mixed income between capital and labout is a well-documented issue for the measurement of labour income. Mixed income is generated primarily by self-employed persons, without registering any split into labour and capital part. (Gollin, 2002; Elsby et al., 2013; Karabarbounis and Neiman, 2014). TO assign mixed income to either either labour or capital income, additional assumptions are needed. The EUKLEMS database assumes self-employed and employed workers have the same hourly wages, on average. This way, mixed income can be split into labour and capital income by using information on the hours worked by self-employed persons.

The Equal hourly wages assumption van lead to issues. Assuming equal hourly wages often causes self-employed labour income be larger than total mixed income. This happens because the actual hourly labour-compensation of the self-employed tends to be lower than that of employed workers. To deal with this problem, I assume instead that all self-employed income is labour income, following the revised estimation methods of Statistics Netherlands (Van Den Bergen et al., 2017). I use the KLEMS data and combine it with data from the OECD on the share of mixed income in total operating surplus, which allows me to make an estimate of mixed income and assign it to labour income.

Next, I show additional details on this correction. For the remainder of the chapter, I use the self-employment corrected labour share series to compute labour and intangible income shares[5].

[5] Note that the decline of the labour share is much smaller when making this correction (see figure 3.2), without this correction, the increase of the intangible share would have been greater, on average.

3.2.2 Mixed Income

To derive the income generated by the self-employed, I start with equation (3.2), which shows that the value added (VA_{cxt}) for industry x in country c at time t is made up of corporate capital income ($r_{cxt}^{corp}K_{cxt}^{corp}$), corporate labour income ($w_{cxt}^{corp}L_{cxt}^{corp}$), mixed income ($M_{cxt}$) - the income generated by the self-employed - and net taxes (τ_{cxt}) paid[6].

$$VA_{cxt} = M_{cxt} + r_{cxt}^{corp}k_{cxt}^{corp} + w_{cxt}^{corp}L_{cxt}^{corp} + \tau_{cxt} \tag{3.2}$$

Given that the mixed income data are not directly observable in the KLEMS dataset, and only available at the country level from the OECD data, the mixed income assigned to each industry is computed using the number of self-employed persons (N^{self}) and the wage of employed persons (w^{corp}), from the KLEMS database:

$$M_{cxt} = M_{ct}\frac{N_{cxt}^{self} * w_{cxt}^{corp}}{\sum N_{cxt}^{self} * w_{cxt}^{corp}} \tag{3.3}$$

I use the national-level value of mixed income (M_{ct}) multiplied by the share of self-employed income (using employed person wages) in the country total. In effect, I assign each industry a share of total national mixed income. Each industry's share of mixed income is determined by the number of self-employed people in the industry, weighted by the industry average wage (for employed persons).

As stated before, I then compute labour income of an industry as the corporate labour income and mixed income of that industry.

$$w_{cxt}L_{cxt} = w_{cxt}^{corp}L_{cxt}^{corp} + M_{cxt} \tag{3.4}$$

Finally, the labour share is the total labour compensation divided by the industry's gross value added:

$$l_{cxt} = \frac{w_{cxt}L_{cxt}}{VA_{cxt}} \tag{3.5}$$

The adjustment for self-employment is relevant over time, as figure 3.2 shows. The graph shows a widening gap between the two series, especially during the 90s. This indicates that using the self-employment correction, the decline of the labour share since the 1980s appears less severe than from the basic KLEMS data. This finding is in concurrence with Elsby et al. (2013), who found a similar disparity for the United States. Specifically, they found that self-employed labour income was slightly overestimated in the 1980s and 90s, but less so later on. This is the reason the labour share decline is less severe when assigning all mixed income to labour income.

The decline of the labour share is reduced across a wider set of countries. Note that in several countries the decline persists, while in others, there is stabilisation, or indeed slight increases. This is in line with the results of Cette et al. (2019). Note that the labour share trend also shows significant variation between industries using either specification.

[6]The data on taxes is not available from the KLEMS database, therefore I abstract away from using taxes.

Figure 3.2: Labour Income Share - Trend across countries (1982=0)

Note: The figure shows the year fixed effects of an (value added weighted) income share regression, which includes industry and country fixed effects.

3.2.3 Capital Income

The tangible capital share consists of income derived from the use of the stock of capital assets in the production of goods and services. Appendix table 3.7 lists the assets used for computing the capital stock. This section deals with the estimation of the income derived from tangible assets, listed in the first two columns of the table[7]. The final two columns of table 3.7 lists the intangibles assets, which will be discussed later. Note that the availability of the data in terms of industry and years differs across different asset types.

The share of capital income is more difficult to estimate than the labour share. Information on labour income is readily collected by national statistical agencies, as the remuneration of employees and other workers (see discussion above). There is usually no discernable income flow registered with the use of capital assets, as most firms own the capital they use in production. [8] The capital income flows therefore tend to remain implicit in total non-labour value added (Hall and Jorgenson, 1967).

To estimate the income associated with the services derived from the use of the capital stock, I follow the common methodology used literature popularised by Hall and Jorgenson (1967). This relies on estimating the rents derived from the use of capital assets based on the costs incurred by owning and using them. This cost, the user cost of capital, consists of three parts. First, the price of purchasing an asset; second, the depreciation cost incurred by using it; third, the price change of the asset, which might make it more, or less valuable.

[7]The list of tangible assets includes most of the important assets, but some notable others are missing. Natural capital like land, as well as inventories of firms, are missing. I am unable to include these due to data constraints.

[8]Unless capital assets are rented. In this case, the costs associated with renting the asset can be considered equivalent to the compensation for the use of labour services.

Because prices and depreciation vary strongly between different assets, the estimation needs to be repeated for each capital asset. Equation (3.6) shows the estimation of capital income derived from tangible capital asset $1, ..., k$ at time t, suppressing country and industry subscripts for notational convenience. Capital income is derived by combining the real capital stock K^k_{cxt} and the cost of capital, $r^k_t K_t$.

$$r^k_t K^k_t = K^k_t * (p^k_{t-1} * \rho^K_t + (p^k_t * \delta^k) - (p^k_t - p^k_{t-1})) \tag{3.6}$$

ρ^k_t is the nominal rate of return on tangible capital assets k, δ^k its depreciation rate and (p^k_t) its investment price. This makes the final term the capital revaluation term[9]. This equation is based on Timmer et al. (2010), and describes the user cost of capital, multiplied by the stock of capital assets[10].

The user cost is an estimate of the rental price of a capital asset, had it been rented from a third party, rather than owned. Multiplying the stocks of all the different tangible capital assets used in production with their respective user costs yields the benefits of the derived capital services. As such, the tangible capital share (k_{cxt}) in country (c) an industry (x) at time (t) is the sum of capital income over all tangible assets, divided by total industry gross value added:

$$k_{cxt} = \frac{\sum_k r^k_{cxt} K^k_{cxt}}{VA_{cxt}} \tag{3.7}$$

The developments of the tangible capital income share are shown in figure 3.3. This figure reveals that assuming a safe rate of return (see next section), the tangible capital share has been on a declining trend since the 1980s across the countries I examine. This result complements the existing literature, which has found a declining tangible capital share in the United States, by showing that it is also declining across a wider set of countries (Barkai, 2016; Karabarbounis and Neiman, 2018).

The results in this section demonstrate that this declining trend of both labour *and* tangible capital incomes shares have occurred across a wider set of advanced countries. If both labour and tangible capital income shares are declining, it must be the case that a growing value added residual remains. Equation (3.8) defines the *intangible* income share f_{cxt} as a residual income share after tangible capital and labour income shares have been accounted for[11].

$$f_{cxt} = F_{cxt}/VA_{cxt} = 1 - k_{cxt} - l_{cxt} \tag{3.8}$$

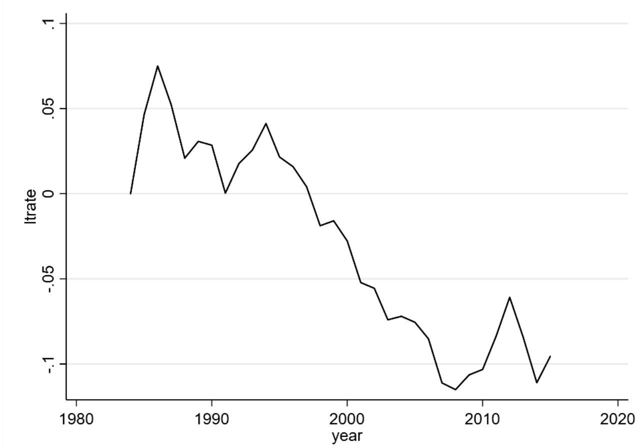
As it is computed as a residual, the intangible income share depends on the assumptions made to estimate tangible capital income. Specifically, two considerations are key: the rate of return on capital assets (ρ^k_{ct}) and the set of assets included in the capital stock (Inklaar, 2010).

[9] I use the actual price change, rather than the firms expected price change of capital, assuming perfect foresight. See also Jorgenson and Vu (2007). Note the revaluation term in Equation (3.6) is specified with a moving average (Gilchrist and Zakrajsek, 2007; Timmer et al., 2010; Inklaar, 2010)

[10] The available data does not contain information on corporate income taxes, property taxes, or investment tax breaks, which I abstract away from. Timmer et al. (2010) argue that the inclusion of taxes makes little difference in the estimation of capital growth rates. For more detail on the inclusion of taxes see Hall and Jorgenson (1967); Inklaar (2010), who use a similar specification for capital income, but also allow for taxes.

[11] The appendix outlines the specific assumption applied when, for example, the intangible share is negative.

Figure 3.3: Tangible Capital Income Share - Trend across countries (1982=0)



Note: The figure shows the year fixed effects of an (value added weighted) tangible capital income share regression, which includes industry and country fixed effects. The figure shows the income share of tangible income using the long-term interest rate (see next section)

These relate to the risk and capital asset narratives presented in Karabarbounis and Neiman (2018), respectively.

Table 3.7 in the appendix gives an overview of the different capital types I employ throughout this chapter. The table lists the sources and shows that the data for different types of assets are available for different periods and industries. The set of tangible assets is smaller starting in the 1980s than when starting in 1995.

Unfortunately, data for several assets are unavailable over the entire period. For example, I am unable to include natural capital assets, even though for some sectors land is an important input for production (Brandt et al., 2017; Inklaar, 2010). The same goes for inventories which might be important in several other sectors (Chen et al., 2017). However, I do not expect the omission of these assets to impact the dynamics of the tangible and intangible capital shares significantly across the board. Furthermore, chapter 4 demonstrates that for most (advanced) countries, the income share of natural capital is very small. Of course, intangible assets might play a key role, especially since the stocks of these assets have grown rapidly (Haskel and Westlake, 2017; Corrado et al., 2005); this matter I return to later.

In the next section, I explore the other consideration, the rate of return. The rate of return on capital assets reflects the risk associated with investing in them. Karabarbounis and Neiman (2018) argue that this could be an important driver of capital share changes. To explore this, I compare two different rates of return and evaluate how they contribute to accounting for the intangible income share.

3.3 Risk & Rate of Return

In this section, I aim to explore how changing risk profiles might impact my estimations of the intangible capital income share. I evaluate the risk aspect by estimating capital income shares based on two different rates of return. The first approximates safe rates of return and reflects a base case where firm rates of return are equal to safe returns. The second rate of return aims to account for risk patterns of firm investments, which might differ strongly from safe returns.

To compute these rates of return, I use data from the Macrohistory database (MHD) (Jordà et al., 2019). First, I use the long-run interest rate (ltrate), which is based on 10-year government bond rates, as a measure for the nominal 'safe' rates of return[12]. This measure, or those based on long-term government bonds, are often used in the literature as they closely approximate returns on safe assets in a country (Inklaar, 2010; Barkai, 2016; Karabarbounis and Neiman, 2018).

Second, I use a weighted average cost of capital (WACC); however, estimates of the WACC are not readily available across countries. As such, I compute The WACC using information on the cost of (government) debt and the cost of (firm) equity, using the macro-history database again to obtain the necessary information. Furthermore, the WACC relies on national level equity-to-debt ratios, which I collect from the OECD[13]. Computing the WACC uses equation (3.9), where C^E and C^D are the costs of equity and debt. These are multiplied with their respective shares implied by the equity-to-debt ratio. The WACC estimates and the long-term interest rates by country are shown in table 3.2 in the next section.

$$WACC = s^E C^E + (1 - s^E) C^D \tag{3.9}$$

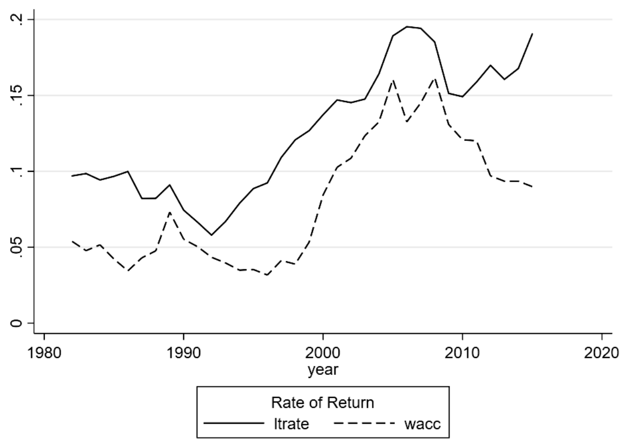
Figure 3.4 shows the intangible income share based on the WACC and the long-term interest rate. The difference between the two rates is an indication of the risk premium. This is because the WACC takes risk into account more fully than the long-term interest rate, which is considered to reflect safe returns (Jordà et al., 2019). The aim of this exercise is to evaluate to what extent the risk premium can account for the increasing intangible income share.

The trends in figure 3.4 are very similar across the two rates, the intangible share has increased on average regardless of the rate. Most of the increase occurred in the 1990s and 2000s. After the mid-2000s, intangible income share growth stagnated for a few years, after which growth continued for the figures based on the long-term rate, but declined for the WACC-based line. Finally, the intangible income share based on the WACC estimates has a lower level throughout the period. This suggests that the WACC can account for some of the levels of intangible income, i.e. less income remains unexplained. However, it is less successful in accounting for the increase of the intangible income share.

[12]The MHD is compiled from different data sources. For the relevant countries, data from the IMF (long term rates) and the OECD (short term rates) are predominantly used. The rates are at the country level, and therefore using them implies assuming that the rate of return is the same across industries. The rates are in nominal terms so I can use them with the standard capital compensation equations for the various types of capital from KLEMS methodology (Timmer et al., 2010) shown in Equation equation 3.6.

[13]I apply a 5-year moving average to filter out the high variation of the cost of equity for the computation of the WACC. Furthermore, I have omitted tax considerations, which might otherwise somewhat reduce the cost of debt due to tax deductibility.

Figure 3.4: Intangible Income Share - Average across countries



Note: The figure shows the year fixed effects of an (value added weighted) intangible capital income share regression, which also includes industry and country fixed effects. The lines show the intangible capital income share using the long term interest rate (ltrate) and the weighted average cost of capital (WACC). Graphs per country are shown in appendix figure 3.7.

Table 3.1 shows the market economy intangible income share and its changes across countries and industries. It covers 2000-2014, as the subsequent analyses of this chapter focus on this period due to data availability constraints from other sources. The table includes estimates based on the long-term rate and the WACC. As apparent from figure 3.4, the estimates based on the WACC are lower than those based on the long-term interest rate.

Taking the WACC estimates to illustrate the differences, average intangible income ranges from 6.9% of GDP in Germany to 17.7% in Italy. Similarly, there are substantial differences in the developments of intangible income across countries too. These range from about -5% to over +5%; the estimated intangible capital income share increased in 6 of the 10 countries. This disparity in changes is similar for the estimates based on the long-term interest rate. These results show that the intangible capital income share is not uniformly rising across countries. This could mean that the underlying drivers of intangible capital income, or their intensity, differ by country too.

A similar story holds for the industry estimates in the bottom panel of table 3.1. The disparities appear larger, especially in terms of levels and changes in several industries are also substantial. The intangible capital income shares are particularly large in the mining and wholesale & retail industries. The reason might be that these industries intensively use inputs unaccounted for in the current data. One of the most important inputs in mining is the actual natural resources they extract, on which data is unavailable. Similarly, the wholesaling and retailing industry intensively use inventories as production inputs (Chen et al., 2017), which are not taken into account[14]. Furthermore, estimates differ quite strongly between the different rates of return. Note that using the long-term interest rate leaves several industries with significant intangible income share increases while using the WACC removes much of these increases.

[14]Chen et al. (2017) argue that some highly internationalised producers of electronics might also sometimes be classified as wholesalers since their production is offshored to such a degree that little manufacturing activities remain in the home country. Such a firm would therefore potentially be classified as wholesale or retail. Since such firms are likely to highly intangible intensive (software, coordination, brand capital and the like) the intangible income of these firms might be high too, further increasing the intangible income estimate of the wholesale industries.

Table 3.1: Intangible Capital Income Share by Country and Industry

	% of Value added (WACC)				% of Value added (ltrate)			
country	Mean	Min	Max	2000-2014	Mean	Min	Max	2000-2014
Austria	12.1	7.4	19.0	-3.0	19.3	13.6	23.3	+4.7
Germany	6.9	4.0	9.7	+2.9	13.0	6.7	17.4	+10.1
Denmark	7.9	4.4	13.4	+0.4	14.8	10.9	19.5	+6.9
Spain	10.7	5.9	15.1	-2.9	16.4	11.1	20.7	-4.1
Finland	11.8	2.9	22.5	+4.4	20.0	13.9	25.7	-2.6
France	11.9	7.0	15.4	-4.6	16.4	14.3	18.2	-3.4
Great Britain	12.5	9.3	15.7	+3.1	15.6	11.2	19.8	+4.8
Italy	17.7	7.9	28.2	-6.0	19.7	12.5	24.5	-6.6
Netherlands	16.7	12.4	19.9	+3.2	21.2	16.1	24.4	+6.9
United States	16.4	12.3	22.6	+1.5	21.6	14.6	26.9	+9.7
Industry	Mean	Min	Max	2000-2014	Mean	Min	Max	2000-2014
Agriculture, forestry and fishing	2.8	0.9	4.8	-1.7	5.9	2.9	12.7	+4.9
Mining and quarrying	47.0	17.6	69.8	+0.5	59.9	34.7	76.4	+18.5
Manufacturing	13.6	9.6	18.4	+2.0	21.4	14.5	26.4	+11.1
Electricity, gas and water supply	15.7	0.9	33.1	-8.3	34.2	22.1	46.3	+5.4
Construction	3.9	1.9	6.2	-0.3	6.1	4.1	8.5	-0.2
Wholesale and retail trade	24.6	21.7	27.6	+3.1	27.9	24.0	31.5	+7.5
Transportation and storage	2.2	0.0	7.1	+0.0	7.1	1.2	12.0	+7.7
Accommodation and food service activities	17.7	12.9	23.5	-3.7	21.6	16.5	25.2	+1.3
Information and communication	15.3	5.8	22.7	+2.1	21.8	7.8	27.5	+12.9
Financial and insurance activities	19.5	11.6	25.9	+4.3	23.3	14.4	28.4	+9.7
Other service activities	3.6	1.5	5.2	-3.2	4.8	3.2	6.3	-2.6

Note: The presented intangible shares are value added weighted averages based on calculations where labour and tangible, but not intangible, capitals are included as factors of production. Country numbers are weighted averages of across industries, while industry numbers are weighted averages of cross-country industry intangible shares. The mean, min and max are the average, lowest, and higher values of the country/industry-level estimates, respectively. The rate of return used for the factor shares shown in the table are indicated in brackets. The changes are in percentage points. Note that the industry estimates are based on more detailed industry data, but shown here in 1-digit ISIC rev.4 industries for expositional convenience.

Choosing different rates of return does not explain the level of intangible income, or its developments fully; however, it can account for some of its increases. Particularly, when I use the WACC, the intangible income level is lowest on average, and changes appear to be the smallest too. This is evidence for the relevance of 'case R' from Karabarbounis and Neiman (2018). However, the rate of return only accounts for a limited part of intangible share dynamics and levels. Additionally, significant variation exists between countries.

Whichever rate of return is assumed, the fact remains that between roughly 4% and as much as 30% of total income is still unaccounted for. Ultimately, the WACC is a more realistic rate of return for firms, as they are not likely investing in safe assets exclusively. Moving forward in this chapter, I use estimates based on the WACC rate of return as the primary specification. The next section integrates the intangible assets from the INTAN-invest database to account for the level, and the heterogeneity of intangible capital income shares.

3.4 Accounting for Intangible Assets

In this section, I explore to what extent intangible assets can account for the intangible income share. I consider two sets of intangible assets, shown in appendix table 3.7. The first are officially recognised in the latest system of national accounts (SNA2008) and hence included in the KLEMS database. Information on prices, capital stocks, and depreciation rates is relatively well established for these intangibles. The other assets were first measured and popularised by Corrado, Hulten & Sichel (2005); as such I refer to them a 'CHS-intangibles'. The data on the CHS-intangibles is from the INTAN-INVEST database (Corrado et al., 2016) and start only in 1995. Fortunately, from figure 3.1, it is clear that the rise in intangible income share took place mostly after 1995, therefore the data still includes the period with the strongest intangible income dynamics.

The CHS-intangibles feature data on intangible assets that are not included as capital assets in national accounts statistics. The data rely on several assumptions, made in the construction of the data. Particularly, the data on depreciation rates, investment prices and own-account investments into intangibles require strong assumptions. For example, the own-account investment into organisational capital is measured as compensation of managers multiplied by a capitalisation factor. For brands and design, own-account investment is not included. See Corrado et al. (2016) for more details on the data construction. Another issue with this data is that much of the EUKLEMS industry detail cannot be maintained, specifically in manufacturing sectors, due to limited industry detail for the CHS-intangible data. Despite these shortcomings, to my knowledge, this is the best data of its kind currently available.

Collectively I refer to the SNA-assets and CHS-assets as the intangible assets. The income generated by intangible assets is derived in the same way as tangible capital income outlined above. Therefore, as per equation (3.6), information on capital formation, stocks, prices, and depreciation rates are required for all of the intangible assets. Capital stocks for CHS-intangibles are not readily included in the database and need to be constructed using the perpetual inventory method (PIM). Equation (3.10) shows how the intangible capital stock B for an intangible asset b is derived from the previous year's stock and gross capital formation I^b (suppressing country and industry subscripts for notational convenience).

$$B_t^b = B_{t-1}^b(1-\delta^b) + I_t^b \tag{3.10}$$

Given equation (3.10), a starting stock in $t = 0$ is required. I follow Chen (2017) in computing the starting stock of capital. It is shown in equation (3.11) (again suppressing country and industry subscripts for notational convenience). The growth rate of capital formation (g) is set to zero throughout the analysis. Since depreciation rates for intangible assets are high, the estimated stocks are relatively insensitive to changes in the starting stock, especially in later periods[15].

$$B_0^b = \frac{I_0^b}{g+\delta^b} \tag{3.11}$$

Because most intangible assets are not recognised as capital in national accounts, investments or cost associated with their production are labelled as intermediate costs, and not included in the total value added of an industry, or in GDP. To remedy this, I adjust value added upwards, reflecting the capital formation of the CHS-intangibles. Equation (3.12) illustrates this by incorporating intangible assets into the equation for value added. $\sum_b r_t^b B_t^b$ is the income derived from intangible asset $1,..,b$. Furthermore, the production value of intangible capital formation $\sum_b p_t^b I_t^b$ for each b are recognised as value added[16].

In this equation, it is possible that some further residual part of income, F^*, remains unaccounted for. However, this residual income differs from intangible income (F) examined above, which was also computed as a residual. F^* reflects income unaccounted for by labour inputs, tangible capital assets, *and* intangible capital assets. In fact, note that if F^* is zero, intangible income F, estimated in the previous section is equal to the income generated by intangible assets minus the value of investments $\sum_b r_t^b B_t^b - \sum_b p_t^b I_t^b$.

$$VA_t + \sum_b p_t^b I_t^b = w_t L_t + r_t^K K_t + \sum_b r_t^b B_t^b + F_t^* \tag{3.12}$$

Having capitalised intangible assets, the next step to evaluate how well these assets can account for the intangible income (F) estimated in the previous section. Assuming that the remaining residual in country c at time t is equal to zero, or $F_{ct}^* = 0$, I derive the rate of return on intangibles assets necessary to fully account for all remaining value added. That is the required rate of return on intangible assets for them to account for all income not already accounted for by labour and tangible capital assets[17]. The advantage of this approach is that I can easily compare the required rates of return on intangible assets to those on tangible assets

[15] Corrado et al. (2009) also make this point, although their run-up period is longer, which makes their stock estimates even less sensitive to the initial stock assumptions.

[16] Following Corrado et al. (2016) the cost of intangible capital formation is taken as the appropriate value of the produced intangible asset. This could be contested as a large part of the intangible capital formation is own-account produced. As such, some mark-up over the cost of production might be appropriate. However, data on such a mark-up is not available, and therefore, to avoid making more arbitrary assumptions, I abstract from it. Note that the KLEMS data already capitalises SNA-intangibles, which are already included in value added. Therefore no additional operations are required, and their addition in equation (3.12) is purely for illustrative purposes.

[17] Figure 3.8 in the appendix shows the development of residual income (F^*) if intangibles are accounted for as in equation (3.1), assigning them the same rate of return as tangible assets.

discussed earlier. Note that it is possible and quite likely that the rate of return on intangible assets is higher than that on tangible assets.

Hansen et al. (2005) argue that due to the nature of intangible assets, their rate of return might well be higher than that of tangible assets. Specifically, the reason to expect such differences is the risk profile of intangible assets. Investments in intangibles might be considerably riskier than tangible assets (Hall, 2001). One reason this might be the case is due to the sunkenness of intangible investments; when investments in intangibles are made, it is very difficult to recoup the investment by selling the intangible asset to someone else (Haskel and Westlake, 2017). This is in contrast with tangible capital, which can be sold more easily, transferring the physical asset.

Along the same lines, many intangible assets like brand capital and organisation capital are highly firm-specific, and might only be valuable in conjunction with other (intangible) assets that the firm possesses. This makes selling them even more complicated. With this in mind, I estimate the rate of return on the intangibles assets that would be necessary to fully account for all intangible income F identified in the previous section.

There are two ways in which I compute the required rate of return on intangible assets (ρ^B). The traditional way using the Jorgenson and Griliches (1967) (JG) method explicitly incorporates intangible assets as factors of production. This method involves specifying a capital income in equation (3.6) for each tangible *and* intangible asset. The final step would then be solving for the unknown (internal) rate of return on intangible assets, assuming the WACC rate of return on tangible assets.

The downside of this method is that it relies heavily on the accuracy of data, including prices and depreciation rates. As outlined above, data quality might vary between the data on tangible capital, the SNA-intangibles, and the CSH-intangibles. Equation (3.13) shows how the required rate of return on intangibles (ρ^{BJG}_{cxt}) using this method is estimated by combining equations (3.12) and (3.6), assuming $F^*_{cxt} = 0$. Country and industry subscripts are suppressed to avoid cluttering the notation.

$$\rho_t^{B_{JG}} = \frac{VA_t + \sum_b (p_t^b I_t^b) - w_t L_t - r_t K_t - \sum_b (B_t^b * (p_t^b * \delta^b - (p_t^b - p_{t-1}^b)))}{\sum_b (B_t^b * p_{t-1}^b)} \tag{3.13}$$

The second way to derive the required rate of return (ρ^B) is suggested by Chen et al. (2017) (CLT). Their method assumes that intangible investment is in steady-state, which means that investments in each intangible asset exactly equal the depreciation of that asset[18]. $\rho^{B_{CLT}}$ can then be estimated as shown in equation (3.14), by dividing intangible income by the value of the stock of intangible assets[19].

$$\rho_t^{B_{CLT}} = \frac{F_t}{\sum_b B_t^b p_t^b} \tag{3.14}$$

[18]The reader is referred to the appendix of Chen et al. (2017) for the detailed derivation.

[19]Equation 3.14 is directly adapted from Chen et al. (2017) and shown here for expositional ease. Because their exposition assumed a different specification of the user cost of (intangible) capital, the actual equation I use is $\rho_{cxt}^{B_{CLT}} = \frac{F_{cxt} - \sum_b (p_t^b - p_{t-1}^b) B^b}{\sum_b B_t^b p_{t-1}^b}$.

Table 3.2: Tangible capital rates of return (WACC & ltrate) and Intangible capital required rates of return (JG & CLT), by country

	Tangible (WACC), % rate of return		Tangible (ltrate), % rate of return		Intangible (JG), % rate of return		Intangible (CLT), % rate of return	
country	2001	2014	2001	2014	2001	2014	2001	2014
Austria	8.5	9.3	5.6	1.5	48.7	49.4	61.0	49.5
Germany	7.6	8.0	5.3	1.2	26.1	35.0	37.8	37.1
Denmark	9.1	12.1	5.6	1.3	7.2	22.2	23.0	31.0
Spain	12.4	9.6	5.5	2.7	125.4	68.1	157.0	81.0
Finland	25.8	8.5	5.5	1.4	9.7	25.6	27.2	29.1
France	11.9	9.3	5.4	1.7	46.9	29.3	57.0	37.6
Great Britain	7.0	6.5	4.9	3.1	35.3	41.7	45.2	44.4
Italy	12.9	8.8	5.6	2.9	58.6	31.7	85.2	39.4
Netherlands	8.2	7.9	5.4	1.5	43.4	43.0	58.4	53.1
Unites States	8.5	10.5	6.0	2.5	25.9	29.0	45.5	39.2

Note: The table shows the rates of return on tangible capital (WACC and ltrate) and the required rates of return on intangibles required if GDP would be fully accounted for by labour, tangible capital, and intangible capital. The two methods outlined in the text, a la Jorgenson and Griliches (1967) (JG) and Chen et al. (2017) (CLT) are shown. The intangible rates of return are based on industry data excluding the agriculture and mining industries

The advantage of the CLT method is that it is less demanding of the data, as it does not require explicit estimation of the income derived from intangible assets. Particularly, this method is less sensitive to measurement error in the depreciation rate of intangible assets. The resulting estimates using either method are shown in columns 3 and 4 of table 3.2 and labelled 'JG' and 'CLT' respectively[20].

The table shows that in most cases, the nominal rate of return required on intangibles to account for all intangible income is very high, occasionally topping 100%. That these are very high is especially obvious when compared to the WACC and long-term rates presented in columns 1 and 2. Again significant differences between countries remain; note the estimated internal rates for Spain, which by far outstrip the others, and the rates for the Scandinavian countries, which tend to be more in line with the rates for tangible assets.

Capitalising intangibles appears insufficient to account for the level of intangible income. Figure 3.8 in the appendix shows the average trend of F^*, the share of income not accounted for by labour, tangible, or intangible assets. The figure illustrates that accounting for intangibles can reduce some of the average rise of the unaccounted income share, generally showing smaller increases and more stable trends than intangible income shown in figure 3.4. However, table 3.2 shows that for income to be accounted for fully, significant variation in the required rates of return on intangible is necessary. This variation indicates that there are still significant intangible income developments unaccounted for by incorporating the current set of intangible assets.

The reason such significant income share (dynamics) remains unaccounted for might be

[20]Throughout this chapter, the rates of return used are country-specific. As such, I show the country level internal rates of return for intangible capital to facilitate comparisons with the rates on tangible assets.

that we are still missing important intangible assets, or due to data quality issues with the intangible assets we have incorporated so far, or both. It is also possible that the difference is due other missing factors like natural capital; land and natural resources (Brandt et al., 2017; Freeman et al., 2020). Similarly, the building of firm inventories might contribute to reducing these estimated rates, but won't likely make up the whole difference and are even less likely to account for the dynamics.

Another possibility is that profits of firms, not derived from the use of any assets could make up the difference. Finally, globalisation likely interacts with intangibles and firm profits, and through them, with the intangible share. Given that the accounting exercise has proven insufficient to understand intangible income dynamics and its sources, in the next section I pursue an econometric approach to relate intangible income to two measures of international trade; offshoring and import competition.

3.5 International Trade & Intangible Income

The previous section demonstrated that intangible income cannot be accounted for by the current standard in intangible asset data. In this section, I perform an alternative analysis using econometric methods to relate international trade to intangible income shares. The period we examine has been one of rapidly deepening trade links and globalisation. Previous literature has found that trade and import competition are positively related to innovation intangibles like R&D (Bloom et al., 2016a) and to intangibles in general (Chen et al., 2017). As such, the increasing importance of international trade may well have led to increases in the income share of intangible assets, and with it the intangible income share.

Figure 3.1 supports this notion as the increase of the share of non-labour, non-tangible capital income was by far strongest during 2000-2008, a period of significant strengthening of trade ties (Escaith et al., 2010). In this section, I discuss the trade-intangible income link, and present two measures of international trade. Finally, I relate these two measures to levels and changes of intangible income shares (f_{cxt}) and the industry-level across countries, and discuss the results.

International trade may affect the intangible income share through offshoring. Chen et al. (2017) argue that value chains which are more internationally fragmented, i.e. cross more borders, tend to have a larger intangible income share on the whole. There are several reasons why this might be the case. These have to do with three specific characteristics of intangible assets.

First, intangible assets are required for successful international operations. In particular firms need communication and coordination intangibles like software, and organisational capital. Second, the high fixed costs and scalability of most intangible assets suggest that the largest (internationalised) firms benefit more from investing in them (Haskel and Westlake, 2017). Think of a particular patent, or organisational know-how. These assets can be extended geographically, without having to invest in them again, as the knowledge has already been generated. This is in contrast with tangible assets, which require (more or less) the same investment in every physical location they are used. The third characteristic is the lack of a required physical location for intangible assets. This means that firms can shift income generated by using their intangible assets abroad back to their home country. This inflates the firm's intangible income in certain locations and vice versa in others[21].

Given these three characteristics of intangible assets, I expect that industries in which offshoring is more prevalent will tend to have higher intangible income shares.

International trade can also be a driver of intangible income through additional competition from abroad. Such competition might pressure firms into lowering mark-ups, which might reduce the intangible income share. Since economic profits are captured in my measure of intangible income, additional international competition might reduce it, by putting pressure of firms' margins. Furthermore, intangible investments often rely on internal financing as it is often difficult to finance them externally due to their sunkenness (Haskel and Westlake, 2017). A reduction in mark-ups and free cash flow might mean less financing will be available for investments into intangibles. This problem is less relevant for investment in tangible capital, as they can be collateralised for external finance.

3.5.1 Offshoring & Import Competition

The first measure of international trade used in this chapter captures offshoring. I use the relative importance of foreign intermediates in the production of each industry. This measure is the share of foreign intermediates and is based on Feenstra and Hanson (1996). Equation 3.15 defines the share of imported intermediate inputs, Ω_{cxt} of industry x in country c, at time t; intermediates sourced from abroad ω^r_{cxt}, divided by total intermediate inputs ω_{cxt}.[22]

$$\Omega_{cxt} = \omega^r_{cxt} / \omega_{cxt} \tag{3.15}$$

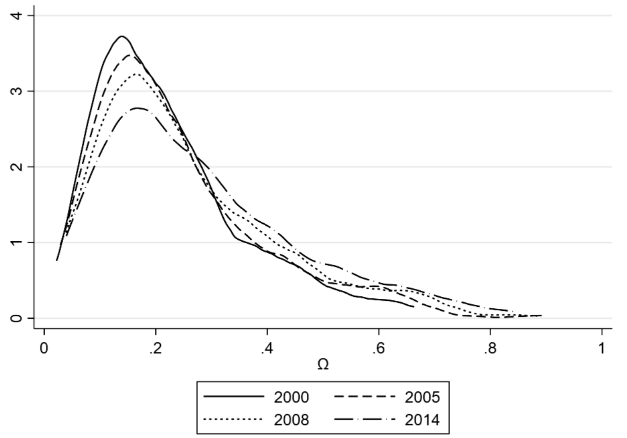
The second measure aims to capture import competition and is based on Los et al. (2016). This method uses Input-Output methods to estimate a counterfactual GDP in the case certain trade linkages would not exist. Doing this for an entire country gives an indication of the importance of trade for that country. The method can provide an answer to the question: How exposed is some industry x in country c to competition from abroad? Using the counterfactual method, competition from abroad is defined as all the value that could have been added by country c's domestic industry x, but due to imports into country c, is added abroad instead. These imports can be both intermediates and final goods, which contain the value that was added by industry x located abroad.

To understand this measure of import competition in terms of imports requires viewing imports in terms of value added. Any imported good/service was produced by combining activities throughout a (global) value chain. In such a chain, different industries contribute to the production of the good/service. As such, any import contains not just value added from the industry of final assembly, but also of all the upstream industries that have contributed previously.

[21] This directly links into a significant problem in the measurement of intangibles in an international operation, profit shifting. This occurs when firms shift profits abroad (for tax reasons), and is discussed in more detail below.

[22] Note that r indicates the rest of the world, i.e. all other countries.

Figure 3.5: Foreign Intermediate Share - Distribution



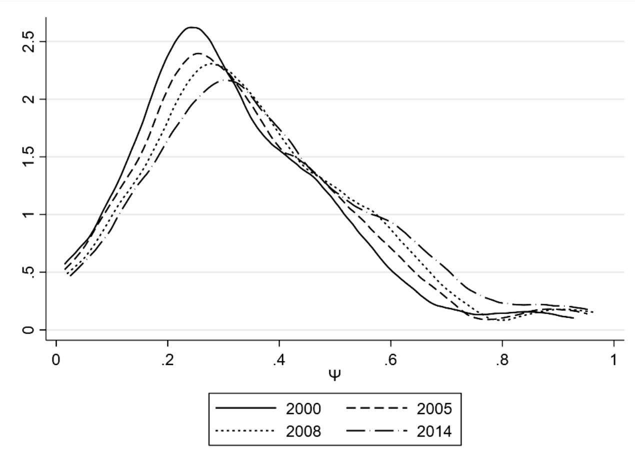
Note: Figure shows the density of Ω across countries and industries at four specific points in time.

As an example, consider the Netherlands importing a t-shirt. A gross import-based measure would assign the full value of this t-shift as import competition for the Dutch apparel industry. However, the imported t-shirt contains value added by many different foreign upstream industries, not just the apparel industry. As such, importing the t-shirt means importing a whole bundle of value, which is added by different industries. This import, therefore, constitutes import competition for all the Dutch industries, whose foreign counterparts have contributed to its production.

The benefit of using this method is that it allows me to decompose the total (gross) imported value into parts of value added by each industry globally. To get at this number, imagine a counterfactual world where country c did not import, i.e. all imports are set to zero. This means that all industries in all countries with direct and indirect trade linkages to c will export less, have less output, and their total value added will be lower compared to their actual observed value added. The total value added of the global industry x will, therefore, also decline. The difference between the observed value added of global industry x and the same value in the counterfactual no-trade case is the value that is added globally in industry x induced by imports of country c.

The import induced value added could hypothetically be produced by industry x in country c, rather than abroad. Therefore, this hypothetical value added, relative to the value added of country c's industry x, indicates how exposed industry x is to imports. This is an indication of how much competition it faces from abroad. Equation (3.16) shows the import competition measure, based on the total industry x value added imported by country c (Imp^*_{cxt}), and the actual domestic value added of industry x in country c (VA_{cxt}). The appendix shows in more

Figure 3.6: Import Competition - Distribution



Note: Figure shows the density of Ψ across countries and industries at four specific points in time.

detail how this measure is derived using input-output methods[23].

$$\Psi cxt = Imp^*_{cxt}/(Imp^*_{cxt} + VA_{cxt}) \tag{3.16}$$

Using Input-Output methods, I can decompose these value bundles, to know for each country the composition of their value added imports. This requires Input-Output data that covers a wide set of countries each linked through trade. For this purpose, I use the 2016 release of the World Input Output Database (WIOD) (Timmer et al., 2016).

The data presented in figure 3.5 shows the distribution of the imported intermediate input share across industries and countries. Figure 3.6 shows the distribution of import competition as computed using the counterfactual method. In these graphs, four lines illustrate the change over time of the distributions. In both cases, by 2014, the concentration of mass shifted to the right and turned into more higher values, indicated by lower peaks, and thicker right-tails. Further country-specific and industry-specific statistics on these variables are listed in appendix table 3.8.

3.5.2 Intangible Income and Trade; levels

To evaluate the relation between the factor income shares and international trade, I use regressions to explore the correlation between the two trade variables and intangible income (F). In the previous section, I have demonstrated that the measured intangible assets are not sufficient to account for intangible income. Additionally, the CHS-intangibles are only available at highly

[23]The imported value, Imp, in equation (3.16) is divided by the sum of Imp and value added so the measure of import competition is between zero and one. This is convenient as the value of imported value added sometimes by orders of magnitudes outstrips domestic value added.

aggregated industry levels, losing much detail. For these reasons, in this section, I focus on exploring the relations between the trade indicators and the income shares of labour, tangible capital, and the intangible income share.

I start by examining the level relations, asking the question; how well can we explain the difference in income shares between different country-industry-time observations. After this, I return to the dynamics, and relate industry income share *changes* to changes in the trade indicators. This latter exercise will aim to explain the dynamics of the intangible income share discussed in the previous sections.

To explore the level relation, I use the regression shown in equation (3.17). Ψ and Ω indicate the measures of import competition and offshoring and η_c, ν_x, χ_t, and ϕ_{ct} are fixed effects. These capture specific effects at the country, industry, and time levels, the final one captures country-time specific effects like national-level business cycles. sh^s_{cxt} is the income share of s (where s is intangible, tangible capital, or labour) in country, industry, year cxt. The results are shown in table 3.3.

$$sh^s_{cxt} = \alpha^s_0 + \alpha^s_1 \Psi_{cxt} + \alpha^s_2 \Omega_{cxt} + \eta^s_c + \nu^s_x + \chi^s_t + \phi^s_{ct} + \epsilon^s_{cxt} \tag{3.17}$$

The regressions in table 3.3 show two distinct relations between trade and intangible income. Specifically, industries that face intense competition from abroad tend to have lower intangible income shares. At the same time, industries in which firms engage in more offshoring tend to have higher intangible income shares[24].

Table 3.3 furthermore shows the relations between trade and the tangible capital income share and the intangible income share have the same sign. Industries facing high levels of import competition tend to have lower tangible capital shares, whereas the tangible capital income share is higher in industries where offshoring is more prevalent. Broadly speaking the intangible and tangibles capital shares result is mirrored by the relation with the labour share. This finding unifies the findings by Autor et al. (2019), who find a positive relationship between import competition and the labour share for United States manufacturing, and the negative offshoring result found by Elsby et al. (2013).

As briefly outlined above, the negative correlation between import competition and the intangible income share could be due to financial constraints faced by firms in highly competitive situations. Intangible investment might suffer more from this than the physical capital investment due problems in obtaining external financing for intangibles (Haskel and Westlake, 2017).

Table 3.4 presents regressions exploring this relation by relating the trade measures to the investment share of intangible assets[25]. The table shows the CHS-intangible assets in the first

[24] The number of observations is slightly less than one would expect from a balanced panel of 23 industries, 10 countries and 15 years (3450), this is because several data points are missing. Particularly, the KLEMS dataset lacks for the USA industry 61 - IT services, and several other data points from industry 19 - oil refining in other countries. Table 3.3 uses intangible and capital shares based on the WACC rate of return. Note that the choice of rate does not matter much for this result. Appendix table 3.9 shows that the result is virtually unchanged when different choices regarding rate of return are made. Note also, that the analysis in table 3.3 does not allow any conclusions about causality. An attempt was made to implement an instrumental strategy similar to Autor et al. (2013), but the multi-country nature of the analysis means this is not feasible

[25] The regressions in table 3.4 use a modified equation (3.17) where the dependent variable is the intangible investment share rather than income shares.

Table 3.3: International Trade & Factor Income Shares

VARIABLES	(1) f_{wacc}	(2) k_{wacc}	(3) l
ImpComp (Ψ)	−0.5544***	−0.1200***	0.7491***
	(0.0292)	(0.0266)	(0.0463)
OffSh (Ω)	0.0850***	0.1298***	−0.2131***
	(0.0295)	(0.0338)	(0.0513)
Constant	0.2930***	0.2804***	0.4026***
	(0.0289)	(0.0209)	(0.0288)
Observations	3,431	3,431	3,431
Adjusted R^2	0.4841	0.5902	0.6257

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The table shows the regressions between the intangible income share, the tangible capital income share, the labour income share, and the trade variables offshoring and import competition. The regressions are unweighted. The regressions use tangible capital and intangible shares based on the WACC return rate.

columns and completes the set with the two most important SNA-intangibles in columns 5 and 6. Note that the number of observations in the former is lower, due to the loss of industry detail by using the CHS-intangibles. The investment share is not the same as the income share of these specific intangible assets. Investment shares more directly reflect firms' actions investing in certain assets. Furthermore, the investment data on intangibles is less reliant on assumptions about depreciation and to some extent prices.

The table shows the negative correlation between import competition and the investment shares of R&D, and advertising, or brand capital. The results support the notion that firms in environments with more international competition tend to have lower intangible investments as a share of total investments for some intangible assets. At the same time, the table shows a significant positive relation between import competition and the shares of training, software capital, and organisational capital. These relations indicate it is not likely that the negative relation between import competition and the intangible share can be fully accounted for by intangible assets. Of course, note again that the quality of the intangible asset data might not (yet) be sufficient for such an exercise.

In addition to import competition, the relation between offshoring and intangible investment shares is also shown. The relationship with R&D is exactly the opposite, suggesting that industries where firms engage in more offshoring, tend also to see more investments into R&D. This result is in line with the findings of Bloom et al. (2016a), who find a positive relation between the China trade shock and innovation in European countries.

The relation between offshoring and organisational capital is positive and significant. This relation makes sense as coordinating international value chains likely requires strong organisational capabilities. Furthermore, offshoring appears positively related to the investment share of most other intangibles too, though these are not statistically significant.

Table 3.4: Import competition, Offshoring and Intangible investment Shares

VARIABLES	(1) Organisational	(2) Brands	(3) Design	(4) Trainings	(5) Software	(6) R&D
ImpComp (Ψ)	−0.0211	−0.0687***	0.1669***	0.0642***	0.0560***	−0.1048***
	(0.0170)	(0.0187)	(0.0422)	(0.0128)	(0.0121)	(0.0189)
OffSh (Ω)	0.0924***	0.0131	0.0362	−0.0222	0.0085	0.0854***
	(0.0196)	(0.0182)	(0.0247)	(0.0163)	(0.0146)	(0.0183)
Constant	−0.0519***	0.0294**	−0.0904***	−0.0257***	0.0142	0.0628***
	(0.0111)	(0.0124)	(0.0219)	(0.0077)	(0.0121)	(0.0118)
Observations	1,760	1,760	1,760	1,760	3,435	3,435
Adjusted R^2	0.8371	0.7902	0.5427	0.7162	0.6916	0.8103

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Table shows the regressions between industry intangible investments shares, and offshoring and import competition. All regressions include time, country, industry, and country-time fixed effects. Note the difference in observations between columns is due to the limited industry detail available for the CHS-intangibles. As such, the regression in columns 1-4 are weighted by the share in total country value added to compensate for industry detail loss, the others are unweighted.

The investment shares are specified between 0 and 1, and the trade variables are also between 0 and 1. So to interpret, for example, the relation between offshoring and software: a 1 ppt higher value in offshoring is associated with a roughly 0.1 percentage-point higher investment share in organisational capital. The highest country-level increase of offshoring over this period happened in the Netherlands and was almost 10 ppt. Therefore, at most, rising offshoring has contributed to an increase of 1 ppt in the investment share of organisational capital. This number is significantly lower in most other countries though.

3.5.3 Intangible Income and Trade; Dynamics

Examining the intangible income share levels is interesting to evaluate differences between industry shares. However, to explore the dynamics that previous sections have outlined, here I examine the development of the industry intangible shares over time. To this end, I adapt equation (3.17) into equation (3.18) and proceed to analyse the relation between *changes* in trade and the intangible share. Equation (3.18) relates the changes of factor shares (Δsh_{cxt}) to the changes in the trade variables ($\Delta\Psi_{cxt}$ and $\Delta\Omega_{cxt}$). The results of the regressions are shown in table 3.5.

$$\Delta sh^s_{cxt} = \alpha^s_0 + \alpha^s_1 \Delta\Psi_{cxt} + \alpha^s_2 \Delta\Omega^s_{cxt} + \eta^s_c + \nu^s_x + \chi^s_t + \phi^s_{ct} + \epsilon^s_{cxt} \tag{3.18}$$

The table shows the same intangible share regression as table 3.3 in the first column, but now using 1-year differences. Column 3 shows the estimates for a reduced, post-global crisis period. And finally, column 4 shows the estimates for the whole period, but using 5-year differences to average out short term fluctuations. Overall, the results are similar in sign and significance to

Table 3.5: International Trade & Factor shares; 2000-2014

VARIABLES	(1) 2000-2014 Δf_{wacc}	(2) 2009-2014 Δf_{wacc}	(3) 2000-2014 (5-year) Δf_{wacc}
Δ ImpComp (Ψ)	−0.8517***	−0.8355***	−0.9456***
	(0.1125)	(0.1581)	(0.1390)
Δ OffSh (Ω)	0.1671**	0.1144*	0.3883***
	(0.0715)	(0.0667)	(0.1025)
Constant	0.0232***	−0.0288**	0.0855***
	(0.0080)	(0.0126)	(0.0200)
Observations	3,200	1,368	685
Adjusted R^2	0.2857	0.2542	0.3833

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The table shows the regressions between change in the intangible income share and offshoring and import competition. All regressions include time, country, industry, and country-time fixed effects. The regressions are unweighted and changes are specified as yearly differences. The regressions use intangible shares based on the WACC rate of return. The number of observations in column 1 is reduced from table 3.3 by a 1-year period due to differencing.

those in levels presented above.

Note however that the positive relation between offshoring and the intangible income share is weaker in the post-global financial crisis period between 2009 and 2014. When I focus on this period in the analysis, the offshoring coefficient is smaller and less statistically significant. This might reflect the post-2008 period of intangible share stability as shown in figure 3.4, during which offshoring seems to have continued to increase as per figure 3.5.

Despite sensitivity to the period, the results are not very sensitive to different weighting schemes. The results in table 3.3 are from unweighted regressions. I do this to evaluate the average industry level relation independent of industry size. Another possibility is to weigh the observations by value added, to evaluate the average relation if larger industries are considered more important. The results of value added-weighted regressions for each rate of return are shown in appendix table 3.9; the conclusions remain unchanged, and the relation between offshoring and intangible income is stronger. These results indicate that the findings are not driven by smaller countries and industries.

Across specifications, the negative coefficient of import competition is larger in absolute terms than the positive coefficient of offshoring, one possible reason for this weaker relation might be transfer pricing. Transfer pricing is when firms shift profits to other (often low-tax) countries through pricing internally traded intermediates such that all gains of accrue in a certain location (Dischinger et al., 2014; Tørsløv et al., 2018). This is very difficult to do with rents accruing to labour and physical capital, given that they are located in particular countries. It is, for example, difficult to pay an American employee's wages in China or rent a machine in Russia to then use it for production in Great Britain. However, intangibles assets have no such

Table 3.6: Intangible Share Differences and Intangible Share Change Differences, Average Explained Country Differences

	Level (%)	Change (%)
Austria	2.70	3.18
Germany	1.44	−0.66
Denmark	8.23	1.59
Spain	−1.47	1.54
Finland	6.85	3.17
France	2.70	−0.44
Gr. Britain	5.18	4.57
Italy	3.54	−1.63
Netherland	−6.01	−2.98
U.S.A.	7.73	1.59

Note: The table shows the average percentage of the intangible share (change) difference between the indicated country and the others, which is explained by the coefficients of offshoring and import competition. The values are weighted by the actual differences in intangible share (change) and only consider the coefficients estimates of offshoring and import competition, the constants and fixed effects are not considered here.

fixed location, and the rents that are derived from their use can relatively easily be 'moved' to any country (Tørsløv et al., 2018). This means that investments in intangibles might not (if at all) be registered in the same country as the rents derived from those intangibles are accruing.

Not only might the transfer pricing problem explain the weaker relation between offshoring and intangible investment, it indicates that the relation between offshoring and the intangible share might be stronger than table 3.3 makes it seem. If profits from intangibles are shifted abroad, domestic intangible income shares should be even greater [26]. It is quite likely that the largest firms benefit the most from intangible assets as they can be scaled across larger operations, and as such yield higher returns (Hansen et al., 2005). This should furthermore be precisely in those industries in which many firms are highly internationalised, as these firms have the most opportunity to shift their profits abroad.

3.5.4 Economic Significance

The results of these analyses indicate the link between trade and intangible income appears quite strong and suggests trade might be an important factor in explaining the differences in terms of intangible shares between industries and countries. Industries that are faced with higher import competition tend to have lower intangible shares, while those in which firms offshore more feature higher intangible shares. These relations are similar in terms of dynamics. Industries where offshoring is increasing, and industries where import competition is decreasing tend to have more rapidly increasing shares of intangible income.

To get an idea of the economic significance of the regression estimates, consider estimated coefficients in tables 3.3 and 3.5. Then, I multiply the estimated coefficients with the average country offshoring and import competition values (changes). This yields for each country the

[26] of course, this depends on the specific country examined. A country to which the profits are shifted towards might experience an inflated relation.

estimated contributions of offshoring and import competition to the intangible income share (change). Table 3.6 reports the average combined estimated contributions as percentages of the actual differences in intangible income shares (changes) from table 3.8. That is to say, for each bilateral country pair, I compare the difference in estimated contributions of offshoring and import competition (change). Then I average these for each country, weighed by the actual bilateral intangible share (change) differences.

Note also that the table does not take country or other fixed effects into account, which results in percentages for some countries that are negative. Such a negative result implies that on average, the actual intangible income share difference is opposite from the predicted difference using the coefficients and values of offshoring and import competition. However, for most countries, the average is positive and between 1.5 and 8.5% for levels and 1.5 and 4.5% for the changes. This gives an idea on average, how much of the cross-country differences in intangible shares (changes) can be explained with the trade measures.

These results indicate that though the numbers are quite small, with the exception of a few countries, the trade measures can make a contribution to explaining the difference in the intangible share *levels* between countries. At the same time, the results aiming to explain the *changes* in intangible income shares appear less successful. With more negative values and smaller percentages overall, these results are less convincing, illustrating the difficulty to explain the dynamics of the intangible income share.

3.6 Conclusion

This chapter documents that intangible - non-labour, non-tangible capital - income as a share of GDP has increased across a set of developed economies since the 1990s. Some of the increase over this period can be accounted for by capitalising intangible capital and considering appropriate rates of return. Accounting for intangible assets, and applying the WACC rate of return limits the increase of intangible income. However, changes in the aggregate and industry dynamics remain, even when applying the most stringent strategies. Similarly, intangible income varies strongly across countries and industries. Considering different rates of return or accounting for intangibles can only explain small parts of this.

These results illustrate the relevance of both accounting for intangible assets and choosing appropriate rates of return in the estimation of capital income, but also show that it is not enough. Accounting for other types of capital, like natural resources or land, or taking capital vintages into account might further refine the results (Gittleman et al., 2003; Inklaar and Papakonstantinou, 2018). Similarly, taking factors like inventories into account might significantly reduce the estimated intangible incomes of specific industries, because it is derived as a residual. Likewise, getting the labour share right is at least as important as it is the largest part of GDP. This could be achieved through additional improvements in its measurement, like a better way to account for self-employed income.

Leaving measurement and the accounting approach aside to explore the dynamics of the intangible income share, I have related its developments to two measures of international trade. To do this, I used a measure of offshoring and introduced a novel measure of import competition.

The results show two relations; (changes in) import competition are negatively related, while (changes in) offshoring are positively related, to (changes in) the intangible income share. These two opposing relations fit a narrative of firm mark-ups, which might be related to high fixed costs of intangible assets, being increased due to offshoring, but suppressed due to international competition. Furthermore, I find tentative evidence that investments in intangible assets might play a role in the relationship between international trade and intangible income. However, given the currently available data on intangibles, it is difficult to make conclusive statements.

In addition to the analyses presented in this chapter, the literature would benefit from more in-depth micro-based explorations of the intangible income share. Studies in the spirit of Autor et al. (2019) and Kehrig and Vincent (2018), using micro-level firm data to dissect factor share developments could significantly enhance our understanding of intangible income dynamics. Such an exploration could reveal that 'superstar-firm dynamics' are driving intangible income dynamics, in the same way, they have been found to drive labour share dynamics (Autor et al., 2019; De Ridder, 2019). This, however, would require highly specific data on capital, depreciation, rates of return, along with the international activities of firms. To my knowledge, such data is at present difficult to obtain, if available at all, let alone for a cross-country investigation. I leave these explorations to future work.

Furthermore, trade is an important factor in rising intangible income shares, therefore I expect studies exploiting the globalising nature of production like Chen et al. (2017) and Los et al. (2016) would greatly aid in researching intangible income. Changing the point of view from the industry level, as I have used throughout this chapter, to a global value chain (GVC) level, might aid the analysis. Using a GVC perspective recognises that production increasingly takes place on a global scale in value chains stretching across (multiple) international borders, rather than nationally. The industry level is interesting from the national point of view, yet GVCs seem to be a more appropriate unit of measure where overall production is concerned.

Examining intangible income at the level of GVCs has an additional benefit. This has to do with the transfer pricing problem. As discussed in the previous section, it is relatively easy for firms utilising global value chains to shift profits to different countries through transfer pricing. In the previous section, I observed that the offshoring development might be positively related to intangible income in national industries, and postulated that this relation might be underestimated due to transfer pricing. A GVC-level analysis could remedy this issue.

Chen et al. (2017) perform a tentative exercise in this spirit and find that global production integration indeed tends to increase the intangible income shares within GVCs. Given the level of aggregation in the data, it remains difficult to say with certainty who is benefiting from gains from intangible investments and where they are located. The nature of the intangible assets from which intangible income is derived might give us an idea. For example, R&D and design are likely done at the very start of the value chain in the home market of some 'lead firm', likewise for advertising and investments in brand capital (Chen et al., 2017).

Note, finally, that the results in this chapter establish correlations, not necessarily causal relationships between trade and intangible income shares. Future research might benefit from exploring novel instrumentation techniques and strategies to establish causal relationships in the exploration of factor income share dynamics.

Appendix

3.A Intangible income share

Equation (3.8) shows how the intangible share of income is derived after labour and tangible capital have been accounted for. However, the combined income of capital and labour could exceed the total recorded value added. This can either be a fluke in the data, an unrealistic assumption about the rate of return, overestimating capital income, or reflect actual negative intangible income. Several cases are possible, generally, I prefer the labour income figures, and take these as a starting point throughout.

In the rare case that labour income itself is larger than value added, I set capital income to be negative, to compensate. This implies capital losses in a given year and might reflect losses being made in an industry. In this case, intangible income is set to zero. This is a very rare case, and most often happens in industries related to mining, which is excluded from my analyses for that reason, among others.

More likely and prevalent, is that both capital and labour income are below one, but together are larger than one. In this case, I take labour income as given, and adjust capital income downwards, to make the capital and labour shares add up to one. This includes the very rare case that capital income is estimated larger than one. In this case, intangible income is again zero.

For these adjustments, the resulting figures for labour, capital, and intangible income are equivalent to those obtained when using an internal rate of return that assumes capital and labour income are exhaustive, and intangible income is zero.

3.B Counterfactual

First, I can use the World Input-Output Database (WIOD) to derive the total value added of each global industry. Particularly, with domestic country c and the rest of the world r, one can think of the different parts of the input-output table as (Notation following Los et al., 2016):

$$A = \begin{bmatrix} Acc & Acr \\ Arc & Arr \end{bmatrix} \tag{3.19}$$

Matrix A is the input coefficient matrix where c is the home country, and r is a collection of the other countries in the world[27]. This matrix contains the input coefficients for all the C countries and X industries. Therefore, matrix A is of $CX * CX$ dimensions. The matrix A_{cc} contains the domestic input coefficients and is of dimension $X * X$. The matrix A_{rc} contains the coefficients for inputs sourced from abroad, this matrix has dimensions $(C-1)X * X$. Finally, $A_r r$, the matrix containing the input coefficients of foreign countries sources from all foreign countries is of dimension $(C-1)X * (C-1)X$.

[27]Before, the notation A was used to indicate the real capital stock of an asset, here, the matrix A denotes, quite unrelated, the input coefficient matrix. This notational duplicate is maintained due to each being the standard in their respective literatures.

$$Y = \begin{bmatrix} Ycc & Ycr \\ Yrc & Yrr \end{bmatrix} \tag{3.20}$$

Is the matrix with final demand. Similarly, Y_{cc} lists domestic final demand for domestically produced final goods, with F final demand categories, it has the dimensions of $X * F$. Y_{rc} contains domestic demand for imported final goods, and is of dimension $(C-1)X * F$ Then to compute the vector of value added in each country-industry, the following equation can be used (Los et al., 2015):

$$VA = \hat{v}(I - A)^{-1}Yq \tag{3.21}$$

In equation (3.22), v is the value added coefficient vector (the hat indicates a diagonal matrix), I is the identity matrix of appropriate size, and q is a summation matrix, that sums over different types of final output. In this setup, the vector VA will contain for each industry in each country the total amount of value added generated. For the current purposes, it is interesting to examine the global value added of each industry across countries. To achieve this, I pre-multiply VA with a matrix that sums over industries, across countries.

$$VA^{sum} = e\hat{v}(I - A)^{-1}Yq \tag{3.22}$$

Where the matrix e is a matrix of $m * nm$ dimensions, summing the value added of each particular industry across countries. The vector VA^{sum} now contains the value added of each industry globally (no longer making the distinction between countries). Having derived the actual value added for each global industry, the estimation of the counterfactual case requires altering both the A and Y matrices, in line with Los et al. (2016). However, instead of removing export linkages as they do, I consider the removal of import linkages. To do this the A and the Y matrices become:

$$A^{*} = \begin{bmatrix} Acc & Acr \\ 0 & Arr \end{bmatrix} \tag{3.23}$$

And

$$Y^{*} = \begin{bmatrix} Ycc & Ycr \\ 0 & Yrr \end{bmatrix} \tag{3.24}$$

Both the imports of intermediate inputs, and imports of final output are set to zero. Using revised matrices, the calculation of the value added vector then becomes:

$$VA^{*} = e\hat{v}(I - A^{*})^{-1}Y^{*}q \tag{3.25}$$

Where each industry's global value added is now calculated, without any imports from the rest of the world (r) to country c. The difference between the values of VA^{*}_{x} and the corresponding values of VA^{sum}_{x} (actual world GDP of each industry) is each global industry's value added generated by the imports of country c.

$$Imp^{*}_{cx} = VA^{sum}_{cx} - VA^{*}_{cx} \tag{3.26}$$

Finally, after excluding the value added domestically in country c, the difference between VA^{sum} (an industries total world value added) and VA^{*} (the counterfactual value added) is the imported value added from each global industry into country c, Imp^{*}_{cx}. Dividing these values by the actual value added of each industry of country c yields the degree to which each of the industries is exposed to imported value. Equation (3.27) shows how the import competition measure is computed. I divide the total imported value by the sum of itself and an industry's actual value added. This is to ensure that the value of import competition always lies between zero and one. This is beneficial as some countries have industries whose imported value added is significantly larger than their own value added.

$$ImpComp_{cx} = Imp^{*}_{cx}/(Imp^{*}_{cx} + VA_{cx}) \tag{3.27}$$

Alternatively, one can construct a counterfactual excluding imports from one country or several countries only, rather than the entire rest of the world. The principles work the same. In this case only certain sub-parts of the A_{rc} and Y_{rc} matrices are set to zero, corresponding to the countries from whom country c hypothetically ceases importing (Los et al., 2016).

3.C Appendix figures & Tables

Table 3.7: Capital Assets; Sources, Availability & Detail

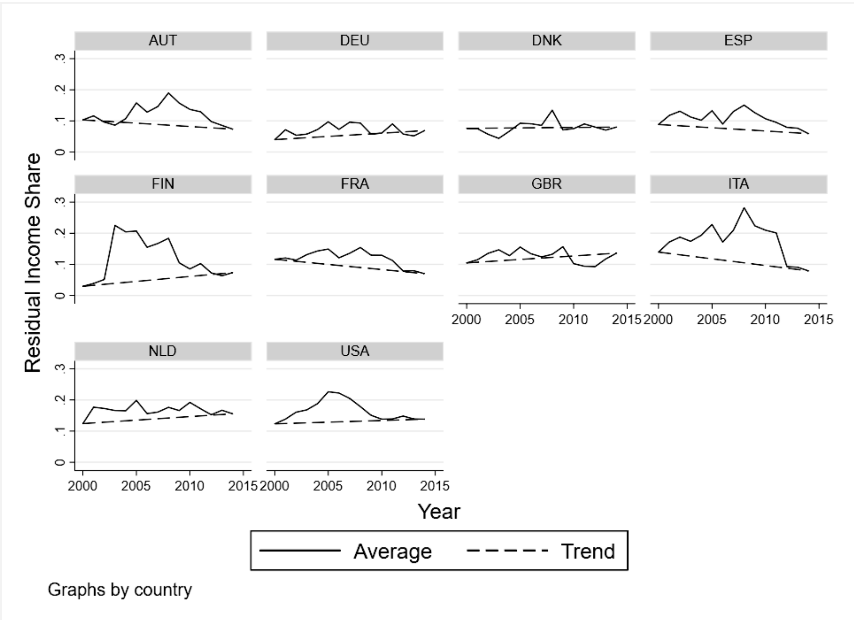
Source		KLEMS		INTAN-invest
Period	1980-2005	1995-2015	1995-2015	1995-2015
ISIC rev. 4	1-digit	2-digit	2-digit	1-digit
Assets	*Tangibles*	*Tangibles*	*SNA-intangibles*	*CHS-intangibles*
	Computing	Computing	Software and Databases	Design
	Communication	Communication	R&D	Financial Products
	Transport	Transport	Mineral exploration	Organisational Capital
	Other Machinery	Other Machinery	Artistic Originals	Brand (Advertising)
	Residential structures	Residential structures		Training
	Non-Res. Structures	Non-Res. Structures		
		Cultivated assets		

Note: The table shows the different capital assets across the various sources employed throughout the chapter . The groups of intangible assets are divided into two set: the "SNA-intangibles" adopted and capitalised in national accounts and the "CHS-intangibles" measured and published by Corrado et al. (2005) as obtained from the INTAN-invest database.

Figure 3.8 shows the development of residual income starting in 1997 when intangible assets are included as capital inputs using the method described above. First, the scale of the residual income share increase is reduced from up to 18 ppt, to at most 6 ppt[28]. Also, the difference between the rates of return has widened too. Regardless, even if the increase of the residual share can be mostly accounted for, not all of the level of residual income is.

[28]It may seem obvious that the inclusion of additional capital assets reduces residual income, but this is not necessarily the case. On the one hand, including additional assets will indeed increase the total income accounted for by capital. On the other hand, recognising new capital assets also means that costs incurred to acquire these assets have to be counted as investments, where before they were counted as costs. This means they now count towards total value added, whereas before they did not. As such, it is entirely possible that recognising new (unproductive) assets as capital might reduce the estimated capital (including both tangible and intangible) income share.

Figure 3.7: Intangible Income Share (f) - Weighted Country Averages



Note: Shows the value added weighted average intangible income share across industries for each country. the figures are based on estimates using the WACC as rate of return. Note that the dramatic increase of Finnish intangible income in 2003 is due to a rise of intangible income across most industries

Table 3.8: Offshoring and Import Competition; Country & Industry details

	Offshoring					Import Competition				
Country	2000	2014	Min	Max	Average	2000	2014	Min	Max	Mean
AUT	0.18	0.21	0.17	0.21	0.19	0.24	0.30	0.24	0.30	0.27
DEU	0.11	0.14	0.10	0.14	0.12	0.21	0.27	0.20	0.27	0.23
DNK	0.27	0.31	0.26	0.32	0.28	0.29	0.34	0.29	0.35	0.32
ESP	0.15	0.10	0.09	0.15	0.12	0.18	0.20	0.16	0.20	0.18
FIN	0.15	0.22	0.15	0.22	0.18	0.26	0.30	0.25	0.31	0.28
FRA	0.11	0.15	0.10	0.15	0.12	0.17	0.21	0.16	0.21	0.18
GBR	0.12	0.13	0.12	0.15	0.13	0.20	0.20	0.19	0.22	0.20
ITA	0.10	0.10	0.09	0.10	0.10	0.18	0.20	0.17	0.20	0.19
NLD	0.21	0.27	0.21	0.27	0.25	0.27	0.34	0.27	0.34	0.30
USA	0.06	0.07	0.05	0.08	0.07	0.10	0.12	0.10	0.13	0.11
ISIC r.4	2000	2014	Min	Max	Mean	2000	2014	Min	Max	Mean
A	0.12	0.15	0.12	0.16	0.14	0.30	0.38	0.29	0.38	0.34
B	0.17	0.20	0.16	0.25	0.22	0.49	0.46	0.46	0.55	0.51
D-E	0.16	0.19	0.15	0.23	0.19	0.20	0.24	0.20	0.27	0.23
F	0.12	0.15	0.11	0.15	0.13	0.03	0.05	0.02	0.05	0.03
G	0.07	0.09	0.07	0.09	0.08	0.12	0.16	0.12	0.16	0.14
H	0.10	0.13	0.10	0.14	0.12	0.21	0.25	0.21	0.26	0.24
I	0.06	0.07	0.06	0.08	0.07	0.06	0.06	0.06	0.07	0.06
K	0.04	0.06	0.04	0.06	0.05	0.10	0.13	0.10	0.15	0.12
M-N	0.07	0.10	0.07	0.10	0.08	0.16	0.18	0.16	0.19	0.17

Note: The table shows the country and industry specific average of offshoring and import competition. Country values are weighted averages of across industries, while industry numbers are weighted averages of cross-country industry value added shares. The mean, min and max are the average, lowest, and higher values of the country/industry-level estimates, respectively. The rate of return used for the factor shares shown in the table are indicated in brackets. The changes are in percentage-points. Note that the industry estimates are based on more detailed industry data, but show here in 1-digit ISIC rev.4 industries for expositional convenience.

Figure 3.8: Residual Income Share (f^*) - Trend across countries & industries, WACC or ltrate

Note: The figure shows the year fixed effects of a residual income (income not accounted for by labour, tangible assets, or intangible assets) share regression (weighted value added), which also includes industry and country fixed effects. Note that the calculations of capital income require two lags; so, while the data starts in 1995, our series starts in 1997.

Table 3.9: Regressions by Rate of Return

VARIABLES	(1) Unweighted f_{wacc}	(2) Unweighted f_{ltrate}	(3) Value added weighted f_{wacc}	(4) Value added weighted f_{ltrate}
ImpComp (Ψ)	−0.5544***	−0.6610***	−0.5304***	−0.6285***
	(0.0292)	(0.0292)	(0.0287)	(0.0286)
OffSh (Ω)	0.0850***	0.0793***	0.1701***	0.0988***
	(0.0295)	(0.0306)	(0.0282)	(0.0301)
Constant	0.2930***	0.3686***	0.2592***	0.3491***
	(0.0289)	(0.0318)	(0.0192)	(0.0254)
Observations	3,431	3,431	3,430	3,430
Adjusted R^2	0.4841	0.5373	0.5719	0.5932

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The table shows the regressions between the intangible income share and the trade variables offshoring and import competition. All regressions include time, country, industry, and country-time fixed effects. The regressions are show the weighted and unweighted specifications as indicated. The regressions use intangible income shares based on the WACC or the ltrate. The difference in observations is due to the weighting scheme.

Chapter 4

International productivity comparisons and natural resources: resource rents and missing endowments*

4.1 Introduction

Development accounting is a popular tool that is used to establish how much of the differences in income levels across countries can be accounted for by differences in observed factor inputs – such as buildings, machinery and (skilled) workers – and how much by differences in productivity, the residual.[1] This, in turn, can inform further research to explain why, for instance, investment in capital may be low or why productivity lags.[2] But omission or mismeasurement of factor inputs will lead to biased measures of productivity. This has motivated researchers to expand and improve the measurement of inputs, by including additional types of intangible capital (Chen et al., 2017), accounting for differences in management practices (Bloom et al., 2016b) and improving estimates of human capital over the life cycle (Lagakos et al., 2018; Inklaar and Papakonstantinou, 2018). Omitted so far in these efforts is the role of natural resources, such as oil, gas, iron and gold, even though natural resources are an important source of income and wealth in many lower-income countries, as well as some (very) high-income countries (Lange et al., 2018).[3] Inputs of subsoil assets are also compatible with the System of National Accounts, which means that systematically accounting for the use of these assets in production does not necessitate changes to measures of output or investment, unlike with, for instance, intangible capital.

The contribution of this chapter is to propose and implement a method for incorporating natural resources as a factor of production in cross-country comparisons of productivity. We build on the work of Brandt et al. (2017) and Diewert and Fox (2016), who show how natural resources can be incorporated in a 'sources of growth' framework. Many of the measurement considerations of their work, such as measures of resource rents, carry through to a cross-country context. However, the extension to a cross-country setting faces a notable challenge in that countries typically extract only a few types of natural resources rather than the full set. Such missing inputs mean that relative productivity is not defined in the typical productivity comparison framework, such as that of Diewert and Morrison (1986) and Inklaar and Diewert (2016).

We propose a solution by drawing a parallel to the literature that deals with the 'new

*This chapter is based on Freeman, Inklaar & Diewert (2019)

[1]See Caselli (2005) and Hsieh and Klenow (2010) for overviews of this literature.

[2]See e.g. Acemoglu et al. (2019), who show that democratization increases income levels by improving investment, not by improving TFP.

[3]More specifically, we focus on what is referred to in National Accounts terminology as 'subsoil assets.' Natural resources more broadly can also cover agricultural land and forests, see Lange et al. (2018).

goods' problem.[4] New goods complicate inflation measurement because no price is observed in the period before the new good appears; a solution is to identify *Hicksian reservation prices* (Hicks, 1940), the price just high enough for demand to be zero. In the current context, we can define a *producer Hicksian reservation price*, which is the input price where that primary input is not used in production. Aside from the practical challenge in identifying what that price level would be, this introduces a conceptual complication in productivity measurement, because in the Diewert and Morrison (1986) framework, a Törnqvist index of primary input quantities is used. When a primary input is missing, this would then require taking the log of zero. To avoid this problem, we will treat natural resources as intermediate inputs.[5] We illustrate this method for incorporating natural resources in international productivity comparisons for the 116 countries for which the Penn World Table (version 9.0, Feenstra et al. (2015)) provides information on the input of produced and human capital and for which Lange et al. (2018) provides information on the production of natural resources – all for the year 2011.

The main unknown variable in applying this method is the reservation price for natural resources. The unit rent – defined as the resource price minus unit production cost – is the central concept, because, as Diewert and Fox (2016) show, the unit rent is equivalent to the user cost of the natural resource, i.e. the price of the input, when beginning-of-period expectations are realised. Estimating a reservation price would typically require knowledge of the parameters of the (factor) demand function. But analysing demand for natural resources simplifies this problem because – in a small open economy – the (country-level) alternative to *extracting* a resource is to *import* it at the world-market resource price. A natural value for the reservation unit rent will thus be resource price, i.e. the cost of importing the resource.

Implementing this method, we find that existing measures of comparative productivity – such as in PWT – are substantially biased in countries where natural resource rents account for a sizeable share of GDP. This is a relatively modest group of countries; for example, only 11 of the 116 countries have a resource rent share of 20 percent of GDP or more. In that group of 11 countries, the average bias in productivity levels (relative to the US) is 36 percent. If one relies on existing productivity measures, countries that have a higher resource rent share show up as more productive. Based on our new measure of productivity that accounts for inputs of natural resources, this is no longer the case. Put differently, resource-rich countries would traditionally show up as uncommonly productive, but this is the result of biased productivity measurement. Our new productivity measure thus more closely approximates a residual measure of cross-country income differences that cannot be accounted for using observable inputs.

The methodology of producer reservation prices we have introduced is relevant beyond the scope of natural resources as missing-goods problems occur in other productivity-measurement settings, too. For instance, microprocessor manufacturing is highly concentrated in a few countries and competition from low-wage countries may mean that in industries such as garment manufacturing, the products produced in high-wage countries are substantially different than in low-wage countries. This issue has so far been ignored in the cross-country industry produc-

[4] See e.g. Diewert and Feenstra (2019); Redding and Weinstein (2016); Feenstra (1994); Balk (1999).

[5] That means that for our productivity computation, the value of output is defined as GDP minus resource rents and inputs consist of labour and produced capital.

tivity comparison literature[6] and can likely be addressed using the producer reservation price tools introduced in this chapter .

4.2 Methodology

In this section we modify the approach for productivity measurement introduced by Diewert and Morrison (1986) – and most recently presented in Inklaar and Diewert (2016) – to a setting where some of the primary input factors are not used by all production units – countries in our setting. We introduce the concept of *producer reservation prices* and adapt the Diewert/Morrison index-number approach to allow this concept to be implemented.

Suppose that we can observe K production units. Assume that the technology set available to unit k is the set S^k for $k = 1, ..., K$.[7] The observed M-dimensional vector of net outputs for unit k is $y^k \equiv (y_1^k, ..., y_M^k)$. If y_m is an output that is being produced by unit k, then $y_m^k > 0$, if it is an input used by unit k then $y_m^k < 0$. The primary inputs used by the production units in the sample are broken up into two groups. The Group 1 input vector for production unit k in period t is $x^k \equiv (x_1^k, ..., x_I^k) \gg 0_I$, a strictly positive vector, which mean the Group 1 inputs are used by all production units in the productivity comparison. The Group 2 input vector for production unit k is $z^k \equiv (z_1^k, ..., z_J^k) \geq 0_J$, a nonnegative vector, which means the Group 2 inputs contain the *missing inputs*.

In the standard Diewert-Morrison formulation, we consider the value-added function for unit k, $^k\,(p, x, z)$ for $p \gg 0_M$:[8]

$$\pi^k\,(p, x, z) \equiv \max_y \left\{p \bullet y\colon (y, x, z) \in S^k\right\}; k = 1, \ldots, K \tag{4.1}$$

We assume that each $\pi^k\,(p, x, z)$ is differentiable with respect to its arguments when evaluated at the data for unit k. Suppose further that production unit k maximizes value added when facing the observed net output prices $p^k \equiv (p_1^k, ..., p_M^k) \gg 0_M$ conditional on having available the Group 1 and 2 vectors of primary inputs, x^k and z^k. Finally, we suppose that unit k faces the vector of Group 1 input prices, $w^k \equiv (w_1^k, ..., w_I^k)$. Using Hotelling's Lemma Hotelling (1932), we have the following relationship between the observed net output vector y^k and the partial derivatives of $\pi^k\,(p, x, z)$ with respect to the components of p^k:

$$y^k = \nabla_p^k \left(p^k, x^k, z^k\right) \tag{4.2}$$

Using Samuelson's Lemma Samuelson (1953),[9] we have the following relationship between the observed Group 1 primary input price vector for unit k, w^k, and the partial derivatives of

[6] See e.g. Inklaar and Timmer (2009) or Jorgenson et al. (2016).

[7] In the Diewert/Morrison framework, the S^k are closed, convex cones with free disposability of inputs and outputs. This setup can easily be generalized to cover not only multiple production units but also multiple periods, see Inklaar and Diewert (2016)

[8] We are assuming that all of the output and intermediate input prices are strictly positive. If there are missing outputs or missing intermediate inputs, we need to estimate positive Hicksian reservation prices for these missing outputs and inputs. We assume that this has been done and these positive reservation prices for the missing outputs and intermediate inputs are included in the strictly positive p vector. See the next section for our approach to determining the Hicksian reservation prices for the zero components of the z vector.

[9] See also Diewert (1974) for a proof of the result.

$\pi^k(p,x,z)$ with respect to the components of x^k:

$$w^k = \nabla_x^k \left(p^k, x^k, z^k\right) \tag{4.3}$$

For the Group 2 primary inputs, the situation is more complex. If Group 2 primary input j is being utilized by production unit k, then let $\omega_j^k > 0$ be the (observed) price for that input. Samuelson's Lemma can be applied to these utilized Group 2 inputs and so the following equations will be satisfied:

$$\omega_j^k = \frac{\partial \pi^k \left(p^k, x^k, z^k\right)}{\partial z_j} \tag{4.4}$$

With j such that $z_j^k > 0$. Equations (4.2), (4.3) and (4.4) can be used as a system of estimating equations if the π^k are given specific functional forms that can be estimated. Once these estimated functions are available, then the *Hicksian reservation price* for the Group 2 inputs j that are missing for unit k are determined from equation (4.4), i.e. the price at which demand for input j in unit k equals zero.

Now it would seem that we can simply apply the Diewert-Morrison exact index number method for estimating productivity differences between any two units using observed prices and quantities for all net outputs and primary inputs that are being used along with the estimated Hicksian reservation prices for the primary inputs that are not being used; i.e. use reservation prices for the inputs that are missing. However, when implementing the Diewert-Morrison methodology, the standard assumption is that the production function is translog, so that relative net outputs can be computed using Törnqvist-Theil price indexes and relative factor inputs using Törnqvist-Theil quantity indexes. Yet when inputs are missing, this would require taking the logarithm of a zero quantity.

A solution to this problem is to shift the Group 2 primary inputs into the intermediate input category; i.e., treat the Group 2 inputs as negative net outputs. This leads us to define the following *modified value-added function*, $\alpha^k(p,\omega,x)$, for unit k where the net output price vectors p is strictly positive and the input price vector is also strictly positive:

$$\alpha^k(p,\omega,x) \equiv \max_{y,z} \left\{p \bullet y - \omega \bullet z \colon (y,x,z) \in S^k\right\}; k = 1,\ldots,K \tag{4.5}$$

The productivity concept for *modified value added* will be relative to the Group 1 primary inputs x instead of the whole range of primary inputs.

Using Hotelling's Lemma, we have the following relationship between the observed net output vector for unit k, y^k, and the partial derivatives of $\alpha^k\left(p^k,\omega^k,x^k\right)$ with respect to the components of p^k:

$$y^k = \nabla_p \alpha^k \left(p^k, \omega^k, x^k\right) \tag{4.6}$$

Using Samuelson's Lemma, we have the following relationship between the observed Group 1 primary input price vector for unit k, w^k, and the partial derivatives of $\alpha^k\left(p^k,\omega^k,x^k\right)$ with respect to the components of x^k:

$$w^k = \nabla_x \alpha^k \left(p^k, \omega^k, x^k\right) \tag{4.7}$$

For the Group 2 primary inputs, we can again distinguish two situations. If Group 2 primary input j is being utilized by production unit k, then, as before, $\omega_j^k > 0$ is the observed price for that input and Hotelling's Lemma can be applied and the following equations will be satisfied:

$$-z_j^k = \frac{\partial \alpha^k \left(p^k, \omega^k, x^k\right)}{\partial \omega_j} \tag{4.8}$$

With j such that $z_j^k > 0$, for a missing Group 2 input, i.e. $z_j^k = 0$, the corresponding price ω_j^k is a *reservation price,* which is not observed but could be estimated using the following equation:

$$0 = \frac{\partial \alpha^k \left(p^k, \omega^k, x^k\right)}{\partial \omega_j} \tag{4.9}$$

Again, with j such that $z_j^k > 0$. Rather than explicitly solving equation (4.9), we will instead choose an approximation to the reservation price. Our main argument will be that the alternative to extracting and processing a natural resource domestically will be to buy it on the world market and pay the world market price to import the metal, oil or gas – the next section discusses this approximation in more detail.

Given reservation prices, we follow Diewert and Morrison (1986) and Inklaar and Diewert (2016) and compare productivity across countries. In doing so, we assume that the modified value-added function of equation (4.5) has a translog functional form with constant returns to scale and constant parameters on the second-order terms. Under that assumption, we can use Törnqvist-Theil indexes to construct output, input and productivity indexes.

Define the value of each net output as $v_m^k \equiv p_m^k y_m^k$ for each unit k and net output $m = 1, \ldots, M$. Likewise, the value of each input in Group 1 is $V_i^k \equiv w_i^k x_i^k$, for each input factor $i = 1, \ldots, I$. The value of each input in Group 2 is $c_j^k = \omega_j^k z_j^k$ for each input $j = 1, \ldots, J$. Having defined these values, the share of each net output (input factor) in the value of total country net outputs (input factors) can be defined as:

$$s_m^k \equiv v_m^k / \left(v^k - c^k\right) \tag{4.10}$$

$$\sigma_j^k \equiv c_j^k / \left(v^k - c^k\right) \tag{4.11}$$

$$S_i^k \equiv V_i^k / V^k \tag{4.12}$$

where $v^k \equiv \sum_{m=1}^{M} v_m^k$, $c^k \equiv \sum_{j=1}^{J} c_j^k$ and $V^k \equiv \sum_{i=1}^{I} V_i^k$ are the total value of net outputs and input factors for each country k. Since we are implementing the modified value-added function of equation (4.5), the Group 2 inputs, which include missing inputs, are treated as part of net output and thus enter in the denominator with a negative sign. By construction, we ensure that $v^k - c^k \equiv V^k$ to be consistent with the assumption of constant returns to scale. Next define the cross-country arithmetic averages of the shares in equations (4.10)-(4.12) as $s_{\cdot m} = \frac{1}{K} \sum_{k=1}^{K} s_m^k$, $\sigma_{\cdot j} = \frac{1}{K} \sum_{k=1}^{K} \sigma_j^k$ and $S_{\cdot i} = \frac{1}{K} \sum_{k=1}^{K} S_i^k$. These average shares, as well as the average prices and quantities, will allow for base-country invariant comparisons of output, inputs and productivity. The price level for modified value added is a Törnqvist-Theil index of net output prices and Group 2 input prices – either observed or reservation prices:

$$lnP^k = \sum_{m=1}^{M} \frac{1}{2}(s_{.m} + s^k_m) ln(\frac{p^k_m}{p_{.m}}) - \sum_{j=1}^{J} \frac{1}{2}(\sigma_{.j} + \sigma^k_j) ln(\frac{\omega^k_j}{\omega_{.m}}) \tag{4.13}$$

Here $\ln p_{.m} \equiv \frac{1}{K}\sum_{k=1}^{K} \ln p^k_m$ and $\ln\omega_{.m} \equiv \frac{1}{K}\sum_{k=1}^{K} \ln\omega^k_m$. Prices in equation (4.13) are expressed relative to a (hypothetical) 'average' country. In further analysis, it is common to express the price level of equation (4.13) with respect to a reference country, such as the United States, i.e. P^k/P^{USA}. Given the price level from equation (4.13), real modified value added Y^k is equal to:

$$Y^k{=}\left(v^k{-}c^k\right)/P^k \tag{4.14}$$

The computation of real factor inputs is broadly analogous, but rather than an aggregate of relative prices, these are computed as a weighted average of relative quantities:

$$\ln X^k{=}\sum_{i=1}^{I} \frac{1}{2}\left(S_{.i}{+}S^k_i\right) \ln\left(\frac{x^k_i}{x_{.\mathrm{i}}}\right) \tag{4.15}$$

Here $\ln x_{.i} \equiv \frac{1}{K}\sum_{k=1}^{K} \ln x^k_i$. The productivity level of unit k is then the ratio of equations (4.14) and (4.15):

$$\Gamma^k{=}\frac{Y^k}{X^k} \tag{4.16}$$

To prepare for our empirical illustration, it is helpful to contrast the productivity measure in equation (4.16) with the measure that is currently used in the Penn World (PWT), see Feenstra et al. (2015). That productivity measure is based on the same Diewert-Morrison theoretical framework, but omits Group 2 inputs, the components of z:[10]

$$\tilde{\Gamma}^k{=}\frac{\tilde{Y}^k}{\tilde{X}^k} \equiv \frac{\left[v^k/\exp\left(\sum_m \frac{1}{2}\left(\tilde{s}_{.m} + \tilde{s}^k_m\right)\ln\left(\frac{p^k_m}{p_{.m}}\right)\right)\right]}{\exp\left(\sum_i \frac{1}{2}\left(\tilde{S}_{.i}{+}\tilde{S}^k_i\right)\ln\left(\frac{x^k_i}{x_{.\mathrm{i}}}\right)\right)} \tag{4.17}$$

This omission has several implications. Equation (4.11), the second term on the right-hand side of equation (4.13), and the c^k in equation (4.14) drop out. Furthermore, the shares in equation (4.10) are redefined to add up to one without input costs c, label these $\tilde{s}^k_m$. More subtly, the adding-up constraint of nominal net output and input costs changes to $v^k \equiv \tilde{V}^k$. In practice, some input costs are readily observable, think of labour compensation of workers. That leaves the cost of produced capital, which will be assigned the residual of total input costs after subtracting the readily-observable input costs, so c^k is added to the costs of produced capital. This leads to an overstatement of the produced-capital share so some of the $\tilde{S}^k_n = V^k_n/\tilde{V}^k$ will

[10]The PWT productivity measure $CTFP$ is based on a bilateral comparison with the United States rather than a multilateral comparison. For a clearer comparison, our biased, PWT-type measure will be the multilateral productivity measure defined in equation (17).

be too large, and some will be too small.
It is thus clear that $\widetilde{\Gamma}^k$ from equation (4.17) is biased relative to the true Γ^k from equation (4.16). The size of the bias will depend on the on the importance of Group 2 income in nominal value added, $\sum_j \sigma_j^k$, in the countries under comparison. Where $\sum_j \sigma_j^k$ is small, the second term on the right-hand side of equation (4.13) can be small (depending on the $\sigma_{\cdot j}$), real value added in equation (4.14) will be similar with or without c^k and $\tilde{S}_i^k \approx S_i^k$, so equation (4.15) based on either set of cost shares will be very similar. If $\sum_j \sigma_j^k$ is not small, there will be a bias in real value added in equation (4.14), from both the numerator $\left(v^k - c^k\right)$ and the denominator P^k. The bias in real input levels from equation (4.15) *need* not be large. If the x_i^k between two countries under comparison are similar, the bias in cost shares will not have a large effect on overall real input levels.
The direction of the bias depends on the reference country. In our results, we will use the United States as the reference country, which means that productivity in any country that relies less on natural resources than the United States, i.e. $\sum_j \sigma_j^k < \sum_j \sigma_j^{USA}$, will tend to be biased downwards when ignoring natural resources and it will typically be biased upwards when $\sum_j \sigma_j^k > \sum_j \sigma_j^{USA}$. Yet given that both real output and real inputs in equation (4.17) differ from those in equation (4.16), the direction of the bias cannot be predicted with certainty from the $\sum_j \sigma_j^k$s.

4.3 Data

To measure productivity, as laid out in equations (4.10)-(4.16), requires data on values of net output and inputs, relative prices, and quantities. Although the general measurement framework applies for any type of units, our focus is on comparing country productivity levels and we want to compare resource-intensive and non-resource-intensive countries as well as countries at different income levels. Thus, the starting point for the dataset is the Penn World Table (PWT), version 9.0, by Feenstra et al. (2015). The dataset we compile for the analysis in this chapter is for the year 2011, the latest year for which direct observations on GDP prices are available, based in large part on World Bank (2015). For 2011, complete data can be compiled for 116 countries, including most of the resource-intensive countries, such as oil- and gas-rich countries in the Middle East, but also mineral-rich countries such as Mauritania and Mongolia.

From PWT, the value of net output v^k equals nominal GDP. The price level of net output, the aggregate over m of p_m^k is the purchasing power parity (PPP) for GDP from PWT. This variable is not constructed as in the first term of equation (4.13) because the available price data are for final expenditure items, rather than for industry net outputs. Yet at the level of GDP, total final expenditure (consumption plus investment plus export minus imports) equals total net output v^k and Feenstra et al. (2015) detail how the price measurement in PWT arrives at the same conceptual outcome as net output in the Diewert-Morrison framework.

Factor inputs x consist of labour and produced capital, so $I = 2$. PWT contains information on the share of labour income in GDP (V_1^k/v^k)[11]. The income flowing to owners of produced

[11] Labour share data are missing for the United Arab Emirates, but due to its resource-intensity, we add it to the dataset assuming $S_L^k = 0.5$, which is comparable to countries in the region. The labour share for Togo in PWT is 85 percent and its resource rent share in GDP is 20 percent, implying negative shares for produced

Table 4.1: Number of countries with positive production for each subsoil asset

Mineral assets	# of countries	Energy assets	# of countries
Bauxite	22	Brown coal	29
Copper	39	Coking coal	22
Gold	74	Thermal coal	41
Iron ore	42	Gas	71
Lead	33	Oil	73
Nickel	19		
Phosphate	34		
Silver	51		
Tin	16		
Zinc	39		

Notes: The total number of countries is 116.

capital will be determined as a residual, $V_2^k = V^k - V_1^k$. The quantity of labour input, x_1^k is based on PWT and measured as total hours worked by all persons engaged, adjusted for differences in educational attainment. The educational attainment adjustment follows Caselli (2005) and is based on the average years of schooling in a country and the (Mincerian) return to education in terms of higher wages. Data on average hours worked is not available from PWT for all countries; where these data are missing, we assume the cross-country mean of average hours worked. The quantity of produced capital, x_2^k is also from PWT. This measure is constructed based on investment by type of asset, adding up to gross fixed capital formation from the National Accounts. Nine asset types are distinguished and the perpetual inventory method with asset-specific deprecation rates is used to construct capital stocks.[12] The current-cost capital stocks are converted to real stocks using a (current-cost capital stock) weighted average of asset-specific PPPs for investment products, from the same data underlying the GDP PPPs. We follow Feenstra et al. (2015) in this measurement, which is certainly subject to caveats[13].

The source of data on natural resources is Lange et al. (2018), whose data cover 15 subsoil assets, consisting of 10 mineral assets and 5 energy assets. The quantity of inputs used, z_j^k is equal to the production of each asset[14] and table 4.1 shows for each of the 15 assets how many countries show positive production levels. Mining of gold, gas and oil are relatively widespread, taking place in 70–74 of the 116 countries, while the other assets are produced in a minority of countries. The median number of assets produced by a country is 4 and 10 of the countries have no subsoil asset production at all. This clearly illustrates the missing input problem that our method sets out to address.

capital. We set $S_L^k = 0.95$ to reflect its high labour intensity, while ensuring positive income to produced capital.

[12] The nine assets are computers, communication equipment, other machinery, transport equipment, residential buildings, other structures, software, other intellectual property products and cultivated assets. Land and inventories are not covered.

[13] It would, for instance, be preferable to include the nine capital assets as separate factor inputs rather than an aggregated stock; see e.g. Inklaar and Timmer (2009) but we focus on the bias in measured productivity from not including natural resources, leaving constant the measurement of other factors.

[14] This production is measured in terms of (tons of) metal or coal, not in terms of ore mined, i.e. production includes the processing of ore. For oil, the production is in barrels of crude oil. For gas, it is in terajoules.

The Lange et al. (2018) data also provide information on the ω_j^k, the input prices. In line with Brandt et al. (2017), the relevant input price for each subsoil asset is taken as the unit rent, the price earned selling the mineral or energy products minus the production costs. As Diewert and Fox (2016) demonstrate, the unit rent is equivalent to the rental price of natural resources when beginning-of-period expectations are realised, thereby providing a price concept that corresponds with standard production theory.

The Lange et al. (2018) data are the only comprehensive global source on resource production, price and production costs, but it is important to note that the available basic data differ by data type, see Lange et al. (2018), Table A.1, p. 214. Production statistics are typically available by country from the International Energy Agency, but other sources are also employed. For many resources, a world resource price is provided in the database, which can be justified from the perspective that these are mostly homogenous products, so price variation should be limited. Unit production costs are typically not available for every country and resource type but instead are described as, for example, 'country-specific case studies from various sources; assumed to be representative for the region'. This suggests that the largest weakness of this source is that the data likely understate the variation in unit rents, but it is unclear whether that would lead to a systematic bias in the productivity measures.

The formal criterion for determining the reservation unit rents is that equation (4.9) should be satisfied, i.e. the reservation unit rent should be such that the optimal $z_j^k = 0$. Estimating factor demand and deriving the unit rent by setting demand equal to zero would entail substantial econometric complications, so instead, we proceed with the following reasoning. Factor demand for natural resources is not about whether, say, oil is used in a country, but instead whether oil is *extracted* in a country. When extracted, the price for that input is equal to the unit rent (when beginning-of-period expectations are realised). The alternative to extraction is importing the mineral or fuel, in which case the price is the resource price on the world market (abstracting from trade costs).

The production sector in country k has a choice between importing one unit of, say, metal j at the world price of R_j per unit of metal or extracting the mineral from a domestic mine and refining it into metal. The per-unit metal cost of the mining and processing of ore j is, say, C_j^k per unit of final metal. If C_j^k is larger than the corresponding world (import) price R_j, then no ore will be mined. If C_j^k is less than the world (import) price R_j, then the ore will be mined, and the rent earned by the production sector of country k will be $u_j^k \equiv R_j - C_j^k$. In the limit, no ore of type j will be mined by country k if $C_j^k = R_j$. Thus, in this case, ore will not be mined and the Hicksian producer reservation price for the natural resource input will be R_j. This argument leads us to define the factor price for ore type j in country k, ω_j^k as follows:

$$\omega_j^k = \begin{cases} u_j^k \equiv R_j - C_j^k & \text{if } R_j > C_j^k \\ R_j & \text{if } R_j < C_j^k \end{cases}$$

Where u_j^k is the unit rent, R_j is the world price of resource j and C_j^k is the cost of extracting resource j in country k. Since C_j^k is not observed when production of a resource equals zero, we operationalise equation (4.17) as $\omega_j^k = \min\left(u_j^k, R_j\right)$.[15]

[15] For most resources, only a single world price is given in the Lange et al. (2018) data. For gas, prices differ by location, between \$4037 and \$6518 per Terajoule and for oil prices differ by type of benchmark, between

Table 4.2: Cross-country distribution of resource rents as a share of GDP

Range	# of countries
<1%	50
≥1% and <5%	29
≥5% and <10%	12
≥10% and <20%	14
≥20%	11

Notes: The total number of countries is 116.

4.4 Results

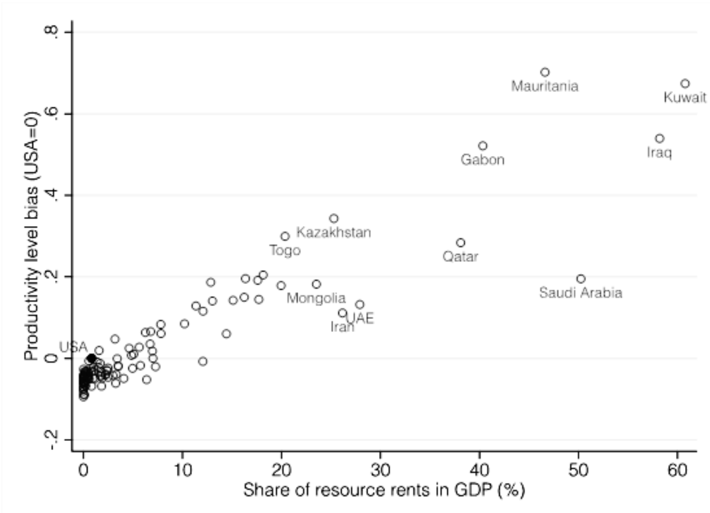
Given factor prices and resource production, we can compute resource rents as a share of GDP, c^k/v^k, to illustrate the importance of natural resources. This provides a first indication of the number countries where we would expect to see a notable bias in their productivity level when omitting natural resources. In table 4.2 we group countries by their resource rent share in GDP and this shows that 50 of the 116 countries have a share of less than one percent of GDP. Even the United States, despite all attention to the boom in shale oil and gas, falls in the 'less than 1%' group. For 11 countries, the share of resource rents is higher than 20 percent of GDP and these include high-income oil-rich countries in the Middle East such as Iran, Iraq, Kuwait, Saudi Arabia and Qatar, but also resource-dependent countries with much lower income levels such as Mauritania, Togo and Mongolia (see table 4.3, below). Another way of illustrating the concentration of resource rents is to note that the top-11 countries in terms of (nominal) resource rents earned account for 80 percent of global resource rents and the bottom-80 countries account for less than 4 percent.

To illustrate the impact of accounting for the input of natural resources on measured productivity, we compute the bias in the relative productivity measure based on equations (4.16) and (4.17), $Bias \equiv \widetilde{\Gamma}^k/\Gamma^k - 1$. In Figure 1, we plot this bias measure against the share of natural resource rents in GDP. As discussed in the methodology section, the bias will tend to be negative when a country's resource rent share is smaller than in the United States, the reference country, and Figure 1 shows that is the case for all countries with smaller resource rent shares. Of the 67 countries with larger resource rent shares, 29 also show a negative bias though it is typically smaller in size. Most notable in this figure are the countries with high resource rent shares, in the 20 percent or higher group from table 4.2. The bias in relative productivity exceeds 10 percent and even reaches more than 50 percent in Iraq, Mauritania and Kuwait.

Table 4.3 shows the results for these resource-intensive countries in more detail, listing the 11 countries in descending order of the resource rent share. The subsequent columns show the newly-developed productivity measure Γ^k (cf. equation (16)) that incorporates natural resources, the measure $\widetilde{\Gamma}^k$ that excludes natural resources (equation (17)) and the measure of bias charted in Figure 1 is shown in the final column of the table. The table shows that the impact

\$86 and \$107 per barrel. In countries with zero production of these assets, we set the world price equal to the maximum observed resource price to reflect (especially in the case of gas) that non-producing countries will face higher prices due to transhipment fees for pipelines or from shipping facilities, such as LNG plants. Productivity levels when selecting the minimum price level instead of the maximum are very similar.

Figure 4.1: Bias in relative productivity when omitting natural resources and the share of natural resource rents in GDP



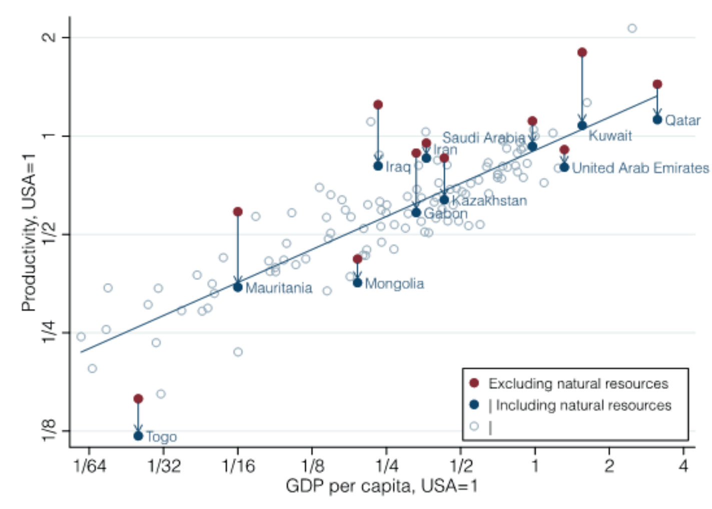
Note: The productivity level bias is defined as $\widetilde{\Gamma}^k/\Gamma^k - 1$, where Γ^k is defined in equation (4.16) and $\widetilde{\Gamma}^k$ is defined in equation (4.17).

Table 4.3: Comparing productivity measures for the top-11 resource-intensive countries

	Resource rent share (% of GDP)	Productivity level (USA=1) Including natural resources, Γ^k	Excluding natural resources, $\widetilde{\Gamma}^k$	Bias, $\widetilde{\Gamma}^k/\Gamma^k - 1$
Kuwait	61	1.15	1.80	0.57
Iraq	58	0.86	1.24	0.45
Saudi Arabia	50	0.97	1.11	0.15
Mauritania	47	0.35	0.59	0.70
Gabon	40	0.60	0.89	0.48
Qatar	38	1.15	1.44	0.25
United Arab Emirates	28	0.80	0.91	0.13
Iran	26	0.87	0.95	0.10
Kazakhstan	25	0.64	0.86	0.33
Mongolia	24	0.35	0.42	0.18
Togo	20	0.12	0.16	0.31
Average	38	0.69	0.94	0.36

Notes: Included are all countries where natural resource rents contribute 20 percent or more to GDP. The resource rent share does not match the data in the World Development Indicators, because our set of natural resources only covers subsoil assets and excludes agricultural land and forests under cultivation.

Figure 4.2: Productivity and income levels – the effect of including natural resources for resource-intensive countries



Note: The figure shows the relationship between productivity levels, including natural resources and GDP per capita for all 116 countries and the linear regression 'line of best fit'. For the 11 most resource-intensive countries, the productivity level excluding natural resources is also included.

on productivity levels is particularly striking in countries where productivity levels exceeded those in the United States when not accounting for natural resources: Kuwait's productivity level decreases from 180 percent to 115 percent of the US level, Iraq's from 124 to 86, Saudi Arabia from 111 to 97 and Qatar's from 144 to 115. More broadly, the average bias across these countries is 36 percent, a substantial adjustment.

As Figure 1 demonstrated, the impact on productivity of accounting for the input of natural resources is most notable for the 11 countries highlighted in that figure and shown in table 4.3 and more modest effects for the other 105 countries. A consequence is that the inclusion of natural resource has a very limited impact on the broader discussion of development accounting. Development accounting assess the degree to which we can account for income differences through measured inputs of human, produced and (now) natural resource capital. This degree can be established, for instance, by regressing (log) productivity levels on (log) income levels. If the slope coefficient of that regression decreases when extending the set of inputs, more of the variation in income levels has been accounted for. Using our results, we find a slope coefficient of 0.335 for both of the productivity measures. Another view on this is that the bias in measured productivity is higher in countries with a higher resource rent share (cf. Figure 1) and the correlation between the resource rent share and (log) GDP per capita is only 0.07.

Given that more general result, Figure 2, shows how the position of the 11 most resource-intensive countries changes when accounting for natural resources. The red solid dots show the productivity levels excluding natural resources and the solid blue dots the productivity levels including natural resources. Not only do all 11 solid dots move down, but in 7 of the 11 cases, they move closer to the regression line. This is a more general result: in the regression of productivity levels, excluding natural resources on income levels, the residuals show a correlation of 0.44 with the resource rent share. In the regression with productivity levels including natural resources, this correlation is –0.03. If we focus on the 105 countries with lower levels of resource rent shares, the correlation decreases from 0.25 to –0.04. Put differently, resource-rich countries used to be uncommonly productive, but after accounting for inputs of natural resources, that is no longer the case.

4.5 Conclusion

The measurement discussion associated with 'missing goods' has typically concentrated on consumer inflation. Prices of newly-introduced products often decline, but the biggest decline may occur at the point of introduction as a previously unobtainable product is suddenly within reach of consumers. To determine the reservation price of this new good, one would typically need to resort to specifying consumer preferences and estimating consumer demand. In this chapter, we analysed a 'missing goods' problem in the setting of cross-country productivity measurement. Mining and processing of subsoil assets such as oil, iron and gold does not occur in every single country, and for good reason: often mining will be a more expensive option than buying the metals or barrels of oil on the world market. This is an attractive feature of this particular case, since it allows us to identify the world price as the reservation price for the input of the natural resource.

Following this argument and adapting the standard cross-country productivity methods to incorporate natural resources, we find that traditional productivity measures – such as included in the Penn World Table – are severely biased for countries that rely heavily on inputs of natural resources, such as Qatar and Saudi Arabia, but also Mauritania and Togo. For these resource-intensive countries, the average bias was 36 percent. More generally, traditional productivity measures suggest that more resource-intensive countries are more productive. We show that this is no longer the case with our newly-developed productivity measure. This measure should thus be seen as a superior alternative to traditional productivity measures that omit natural resources from the set of inputs.

More broadly, this chapter has focused on the fact that missing-goods problems can also occur in the context of productivity measurement instead of solely being a consumer inflation problem. In measuring prices over time, the aggregate effect of the missing-good problems can be limited as a new good is initially not consumed very intensively. Yet in comparing productivity across countries, there can be many countries where the good in question is not missing and we have shown that the bias from ignoring this problem can be substantial. We can think of several other situations where this may occur. For instance, some countries may have started investing in computers and software much sooner than others. But this problem may be most severe for the output side of productivity accounts. For example, the dominant producer of microprocessor units is Intel and the firm only operates wafer fabrication sites in the United States, Ireland, Israel and China,[16] while other countries specialise in different types of semiconductors. This problem can also occur in lower-tech industries, such as garments. High-wage countries still retain a garment industry and this industry may survive by focusing on higher-quality products but also by focusing on different products than firms in low-wage countries. These settings would also be amenable to the logic we employed in choosing reservation prices for natural resources, i.e. use the import price of the non-produced product as the reservation price. We hope this producer reservation price methodology can serve as a useful new tool for productivity researchers faced with missing-goods situations.

[16] As documented at $https://www.intel.com/content/www/us/en/architecture-and-technology/global-manufacturing.html$, accessed on November 7, 2018.

Bibliography

Acemoglu, D., Naidu, S., Restrepo, P., and Robinson, J. A. (2019). Democracy does cause growth. *Journal of Political Economy*, 127(1):47–100.

Acemoglu, D. and Restrepo, P. (2016). The Race Between Machine and Man: Implications of Technology for Growth, Factor Shares and Employment. *NBER working papers*, 22252:1–30.

Acemoglu, D. and Restrepo, P. (2018a). Artificial intelligence, automation and work. Working Paper 24196, National Bureau of Economic Research.

Acemoglu, D. and Restrepo, P. (2018b). Modeling Automation. *American Economic Association Papers and Proceedings*, 108(54):48–53.

Adrjan, P. (2018). The mightier, the stingier: Firms' market power, capital intensity, and the labor share of income. Technical report, University Library of Munich, Germany.

Aghion, P., Bergeaud, A., Boppart, T., Klenow, P. J., and Li, H. (2019). A theory of falling growth and rising rents. Working Paper 2019-11, Federal Reserve Bank of San Francisco.

Akcigit, U. and Ates, S. T. (2019). Ten facts on declining business dynamism and lessons from endogenous growth theory. Working Paper 25755, National Bureau of Economic Research.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., and Van Reenen, J. (2017, revised 2019). The fall of the labor share and the rise of superstar firms. Working Paper 23396, National Bureau of Economic Research.

Autor, D. and Salomons, A. (2018). Is automation labor share–displacing? productivity growth, employment, and the labor share. *Brookings Papers on Economic Activity*.

Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review*, 103(6):2121–68.

Balk, B. M. (1999). *On curing the CPI's substitution and new goods bias*. CBS.

Barkai, S. (2016). Declining labor and capital shares. *Stigler Center for the Study of the Economy and the State New Working Paper Series*, 2.

Blanchard, O. and Giavazzi, F. (2003). Macroeconomic effects of regulation and deregulation in goods and labor markets. *The Quarterly Journal of Economics*, 118(3):879–907.

Bloom, N., Draca, M., and Van Reenen, J. (2016a). Trade induced technical change? The impact of chinese imports on innovation, IT and productivity. *Review of Economic Studies*, 83(1):87–117.

Bloom, N., Sadun, R., and Van Reenen, J. (2016b). Management as a technology? Technical report, National Bureau of Economic Research.

Brandt, N., Schreyer, P., and Zipperer, V. (2017). Productivity measurement with natural capital. *Review of Income and Wealth*, 63:S7–S21.

Bridgman, B. (2017). Is labor's loss capital's gain? Gross versus net labor shares. *Macroeconomic Dynamics*, pages 1–18.

Brynjolfsson, E., McAfee, A., Sorell, M., and Zhu, F. (2008). Scale Without Mass: Business Process Replication and Industry Dynamics. SSRN Scholarly Paper ID 980568, Social Science Research Network, Rochester, NY.

Brynjolfsson, E., Rock, D., and Syverson, C. (2018). The productivity j-curve: How intangibles complement general purpose technologies. Working Paper 25148, National Bureau of Economic Research.

Calligaris, S., Criscuolo, C., and Marcolin, L. (2018). Mark-ups in the digital era. OECD Science, Technology and Industry Working Papers 2018/10.

Caselli, F. (2005). Accounting for cross-country income differences. *Handbook of economic growth*, 1:679–741.

Cennamo, C. and Santalo, J. (2013). Platform competition: Strategic trade-offs in platform markets. *Strategic Management Journal*, 34(11):1331–1350.

Cette, G., Corde, S., and Lecat, R. (2017). Stagnation of productivity in France: a legacy of the crisis or a structural slowdown? *Economie et Statistique / Economics and Statistics*, (494-495-496):11–36.

Cette, G., Koehl, L., and Philippon, T. (2019). Labor shares in some advanced economies. Working Paper 26136, National Bureau of Economic Research.

Chen, W. (2017). Cross-Country Income Differences Revisited: Accounting for the Role of Intangible Capital. *Review of Income and Wealth*, (00):1–23.

Chen, W., Los, B., and Timmer, M. (2017). Factor Incomes in Global Value Chains: The Role of Intangibles. In *Measuring and Accounting for Innovation in the 21st Century*, NBER Chapters. National Bureau of Economic Research, Inc.

Ciminelli, G., Duval, M. R. A., and Furceri, D. (2018). *Employment Protection Deregulation and Labor Shares in Advanced Economies*. International Monetary Fund.

Corrado, C., Haskel, J., Jona-Lasinio, C., and Iommi, M. (2014). Intangibles and industry productivity growth: Evidence from the EU. In *Manuscript available at www. intan-invest. net*, Rotterdam. International Association for Research in Income and Wealth.

Corrado, C., Haskel, J., Jona-Lasinio, C., and Iommi, M. (2016). Intangible investment in the EU and US before and since the Great Recession and its contribution to productivity growth. Technical report, EIB Working Papers.

Corrado, C., Haskel, J., Massimiliano, I., Jona-Lasinio, C. S., Mas, M., and O'Mahony, M. (2017). Advancements in measuring intangibles for european economies.

Corrado, C., Hulten, C., and Sichel, D. (2005). Measuring Capital and Technology: An Expanded Framework. In Corrado, C., Haltiwanger, J., and Sichel, D., editors, *Measuring Capital in the New Economy*, NBER Book Series Studies in Income and Wealth, pages 11 – 46. University of Chicago Press.

Corrado, C., Hulten, C., and Sichel, D. (2009). Intangible Capital and U.S. Economic Growth. *Review of Income and Wealth*, 55(3):661–685.

Dao, M. C., Das, M. M., Koczan, Z., and Lian, W. (2017). *Why is labor receiving a smaller share of global income? Theory and empirical evidence*. International Monetary Fund.

De Loecker, J. and Eeckhout, J. (2018). Global market power. Working Paper 24768, National Bureau of Economic Research.

De Loecker, J., Eeckhout, J., and Unger, G. (2017, revised 2018a). The Rise of Market Power and the Macroeconomic Implications. *NBER Working Paper Series*, page 44.

De Loecker, J., Fuss, C., and Biesebroeck, J. V. (2018b). Markup and price dynamics: linking micro to macro. Working Paper Research 357, National Bank of Belgium.

De Loecker, J., Goldberg, P. K., Khandelwal, A. K., and Pavcnik, N. (2016). Prices, markups, and trade reform. *Econometrica*, 84(2):445–510.

De Loecker, J. and Warzynski, F. (2012). Markups and Firm-Level Export Status. *The American Economic Review*, 102(6):2437–2471.

De Ridder, M. (2019). Market power and innovation in the intangible economy. Working Paper 2019-07, Centre for Macroeconomics.

Decker, R. A., Haltiwanger, J., Jarmin, R. S., and Miranda, J. (2017). Declining Dynamism, Allocative Efficiency, and the Productivity Slowdown. *American Economic Review*, 107(5):322–326.

Decker, R. A., Haltiwanger, J. C., Jarmin, R. S., and Miranda, J. (2018). Changing business dynamism and productivity: Shocks vs. responsiveness. Working Paper 24236, National Bureau of Economic Research.

Deelen, A., Kuijpers, S., and Prins, T. (2018). Loongroei, een analyse op bedrijvendata. Cpb achtergronddocument, CPB.

Diewert, W. E. (1974). *Applications of duality theory*. Stanford Institute for Mathematical Studies in the Social Sciences.

Diewert, W. E. and Feenstra, R. C. (2019). Estimating the benefits of new products. Working Paper 25991, National Bureau of Economic Research.

Diewert, W. E. and Fox, K. J. (2016). The user cost of nonrenewable resources and green accounting. In *Society for Economic Measurement Conference, OECD, and the Workshop on Environmentally Adjusted Productivity and Efficiency, University of Sydney*, volume 22.

Diewert, W. E. and Morrison, C. J. (1986). Adjusting Output and Productivity Indexes for Changes in the Terms of Trade. *The Economic Journal*, 96(383):659–679.

Dischinger, M., Knoll, B., and Riedel, N. (2014). The role of headquarters in multinational profit shifting strategies. *International Tax and Public Finance*, 21(2):248–271.

DNB (2018). Achtergrondnotitie bij DNBulletin "Flexibilisering ar beidsmarkt gaat gepaard met daling arbeidsinkomensquote". Technical report, De Nederlandse Bank, Amsterdam.

Doraszelski, U. and Jaumandreu, J. (2013). R & d and productivity: estimating endogenous productivity. *Review of Economic Studies*, 80(4):1338–1383.

Döttling, R., Gallardo, G., and Philippon, T. (2017). Is there an investment gap in advanced economies? if so, why? *Unpublished Working Paper, SSRN.*

Duarte, F. and Rosa, C. (2015). The equity risk premium: a review of models. *Economic Policy Review*, (2):39–57.

Economist (2005). Keep seatbelts fastened during ascent. The Economist online.

Eggertsson, G. B., Robbins, J. A., and Wold, E. G. (2018). Kaldor and piketty's facts: The rise of monopoly power in the united states. Working Paper 24287, National Bureau of Economic Research.

Elsby, M. W., Hobijn, B., and Şahin, A. (2013). The decline of the US labor share. *Brookings Papers on Economic Activity*, 2013(2):1–63.

Escaith, H., Lindenberg, N., and Miroudot, S. (2010). International supply chains and trade elasticity in times of global crisis. *World Trade Organization (Economic Research and Statistics Division) Staff Working Paper ERSD-2010-08.*

Faggio, G., Salvanes, K. G., and Reenen, J. V. (2010). The evolution of inequality in productivity and wages: panel data evidence. *Industrial and Corporate Change*, 19(6):1919–1951.

Farhi, E. and Gourio, F. (2018). Accounting for macro-finance trends: Market power, intangibles, and risk premia. *Brookings Papers on Economic Activity*, 2018(2):147–250.

Feenstra, R. C. (1994). New product varieties and the measurement of international prices. *The American Economic Review*, pages 157–177.

Feenstra, R. C. and Hanson, G. H. (1996). Globalization, Outsourcing, and Wage Inequality. *American Economic Review*, 86(2):240–245.

Feenstra, R. C., Inklaar, R., and Timmer, M. P. (2015). The next generation of the penn world table. *American Economic Review*, 105(10):3150–3182.

Freeman, D., Inklaar, R., and Diewert, W. E. (2020). International productivity comparisons and natural resources: resource rents and missing inputs. *Review of Income and Wealth*.

Gandhi, A., Navarro, S., and Rivers, D. (2017). How heterogeneous is productivity? a comparison of gross output and value added. University of Western Ontario, Centre for Human Capital and Productivity (CHCP) Working Papers 201727, University of Western Ontario, Centre for Human Capital and Productivity (CHCP).

Gilchrist, S. and Zakrajsek, E. (2007). Investment and the cost of capital: New evidence from the corporate bond market. Working Paper 13174, National Bureau of Economic Research.

Gittleman, M., ten Raa, T., and Wolff, E. N. (2003). The vintage effect in tfp growth: An analysis of the age structure of capital. Working Paper 9768, National Bureau of Economic Research.

Gollin, D. (2002). Getting Income Shares Right. *Journal of Political Economy*, 110(2):458–474.

Grossman, G. M., Helpman, E., Oberfield, E., and Sampson, T. (2017). The productivity slowdown and the declining labor share: A neoclassical exploration. Working Paper 23853, National Bureau of Economic Research.

Guschanski, A. and Onaran, O. (2018). The labour share and financialisation: Evidence from publicly listed firms. Greenwich Papers in Political Economy 19371, University of Greenwich, Greenwich Political Economy Research Centre.

Guscina, A. (2006). Effects of globalization on labor's share in national income. *IMF, Working Paper*, (06/294).

Gutierrez, G. (2017). Investigating global labor and profit shares. *Unpublished Working Paper, SSRN*.

Gutiérrez, G. and Philippon, T. (2017). Declining Competition and Investment in the US. NBER Working Paper No. 23583, National Bureau of Economic Research.

Hall, R. E. (1988). The Relation between Price and Marginal Cost in U.S. Industry. *Journal of Political Economy*, 96(5):921–947.

Hall, R. E. (2001). The stock market and capital accumulation. *American Economic Review*, 91(5):1185–1202.

Hall, R. E. and Jorgenson, D. W. (1967). Tax policy and investment behavior. *American Economic Review*, 57(3).

Hansen, L. P., Heaton, J. C., and Li, N. (2005). Intangible risk. In *Measuring Capital in the New Economy*, pages 111–152. University of Chicago Press.

Harrison, A. (2005). Has globalization eroded labor's share? Some cross-country evidence. MPRA paper no. 39649, University Library of Munich, Germany.

Haskel, J. and Westlake, S. (2017). *Capitalism without Capital: The Rise of the Intangible Economy*. Princeton University Press.

Hicks, J. R. (1940). The valuation of the social income. *Economica*, 7(26):105–124.

Hopenhayn, H. A. (1992). Entry, exit, and firm dynamics in long run equilibrium. *Econometrica: Journal of the Econometric Society*, pages 1127–1150.

Hotelling, H. (1932). Edgeworth's taxation paradox and the nature of demand and supply functions. *Journal of Political Economy*, 40(5):577–616.

Hsieh, C.-T. and Klenow, P. J. (2010). Development accounting. *American Economic Journal: Macroeconomics*, 2(1):207–23.

Hsieh, C.-T. and Rossi-Hansberg, E. (2019). The industrial revolution in services. Working Paper 25968, National Bureau of Economic Research.

Inklaar, R. (2010). The sensitivity of capital services measurement: Measure all assets and the cost of capital. *Review of Income and Wealth*, 56(2):389–412.

Inklaar, R. and Diewert, W. E. (2016). Measuring industry productivity and cross-country convergence. *Journal of Econometrics*, 191(2):426–433.

Inklaar, R. and Papakonstantinou, M. (2018). Vintage effects in human capital: Europe versus the united states. *Review of Income and Wealth*.

Inklaar, R. and Timmer, M. P. (2009). Productivity Convergence Across Industries and Countries: the Importance of Theory-Based Measurement. *Macroeconomic Dynamics*, 13(S2):218.

Jones, C. I. (2016). The facts of economic growth. In *Handbook of macroeconomics*, volume 2, pages 3–69. Elsevier.

Jordà, Ò., Knoll, K., Kuvshinov, D., Schularick, M., and Taylor, A. M. (2019). The rate of return on everything, 1870–2015. *The Quarterly Journal of Economics*, 134(3):1225–1298.

Jorgenson, D. W. and Griliches, Z. (1967). The explanation of productivity change. *Review of Economic Studies*, 34(3):249–283.

Jorgenson, D. W., Nomura, K., and Samuels, J. D. (2016). A half century of trans-pacific competition: Price level indices and productivity gaps for japanese and us industries, 1955-2012. In *The World Economy: Growth or Stagnation?*, pages 469–507. Cambridge University Press.

Jorgenson, D. W. and Vu, K. (2007). Information technology and the world growth resurgence. *German Economic Review*, 8(2):125–145.

Jäger, K. (2017, revised 2018). EU KLEMS Growth and Productivity Accounts 2017 Release, Statistical Module. Background document.

Kaldor, N. (1957). A Model of Economic Growth. *The Economic Journal*, 67(268):591–624.

Karabarbounis, L. and Neiman, B. (2014). The global decline of the labor share. *The Quarterly Journal of Economics*, 129(1):61–103.

Karabarbounis, L. and Neiman, B. (2018). *Accounting for Factorless Income*, pages 167–228. University of Chicago Press.

Kehrig, M. and Vincent, N. (2018). The micro-level anatomy of the aggregate labor share decline. *NBER Working Paper No. 25275.*

Keynes, J. M. (1939). Relative movements of real wages and output. *The Economic Journal*, 49(193):34–51.

Koh, D., Santaeulalia-Llopis, R., and Zheng, Y. (2016, revised 2019). Labor share decline and intellectual property products capital. (927).

Krueger, A. B. (1999). Measuring labor's share. *American Economic Review*, 89(2):45–51.

Kuznets, S. (1955). Economic growth and income inequality. *The American economic review*, 45(1):1–28.

Lagakos, D., Moll, B., Porzio, T., Qian, N., and Schoellman, T. (2018). Life cycle wage growth across countries. *Journal of Political Economy*, 126(2):797–849.

Lange, G.-M., Wodon, Q., and Carey, K. (2018). *The changing wealth of nations 2018: Building a sustainable future.* The World Bank.

Los, B., Timmer, M. P., and de Vries, G. J. (2015). How global are global value chains? A new approach to measure international fragmentation. *Journal of Regional Science*, 55(1):66–92.

Los, B., Timmer, M. P., and De Vries, G. J. (2016). Tracing value-added and double counting in gross exports: Comment. *American Economic Review*, 106(7):1958–1966.

Lucas Jr, R. E. (1978). On the size distribution of business firms. *The Bell Journal of Economics*, pages 508–523.

McAdam, P., Petroulakis, F., Vansteenkiste, I., Cavalleri, M. C., Eliet, A., and Soares, A. (2019). Concentration, market power and dynamism in the euro area. Working Paper Series 2253, European Central Bank.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *econometrica*, 71(6):1695–1725.

Melitz, M. J. and Polanec, S. (2015). Dynamic Olley Pakes productivity decomposition with entry and exit. *The Rand journal of economics*, 46(2):362–375.

Milanovic, B. (2016). Increasing capital income share and its effect on personal income inequality. LIS Working papers 663, LIS Cross-National Data Center in Luxembourg.

Oberfield, E. and Raval, D. (2014). Micro data and macro technology. Working Paper 20452, National Bureau of Economic Research.

OECD (2018). *OECD Employment Outlook 2018*.

Olley, G. S. and Pakes, A. (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica*, 64(6):1263.

Philippon, T. (2018). A Primer On Concentration, Investment and Growth. Jackson Hole, USA. Federal Reserve Bank of Kansas City.

Piketty, T. (2015). About capital in the twenty-first century. *American Economic Review*, 105(5):48–53.

Piketty, T. and Zucman, G. (2014). Capital is back: Wealth-income ratios in rich countries 1700–2010. *The Quarterly Journal of Economics*, 129(3):1255–1310.

Redding, S. J. and Weinstein, D. E. (2016). A unified approach to estimating demand and welfare. LSE Research Online Documents on Economics 67681, London School of Economics and Political Science, LSE Library.

Resheff, A. and Santoni, G. (2019). Are your labor shares set in beijing? the view through the lens of global value chains. Working paper series, Paris School of Economics.

Rognlie, M. (2016). Deciphering the Fall and Rise in the Net Capital Share: Accumulation or Scarcity? *Brookings Papers on Economic Activity*, 2015(1):1–69.

Rossi-Hansberg, E., Sarte, P.-D., and Trachter, N. (2018). Diverging trends in national and local concentration. Working Paper 25066, National Bureau of Economic Research.

Samuelson, P. A. (1953). Prices of factors and good in general equilibrium. *The Review of Economic Studies*, 21(1):1–20.

Timmer, M., Dietzenbacher, E., Los, B., Stehrer, R., and de Vries, G. (2015). An Illustrated User Guide to the World Input–Output Database: the Case of Global Automotive Production. *Review of International Economics*, 23(3):575–605.

Timmer, M. P., Erumban, A. A., Los, B., Stehrer, R., and de Vries, G. J. (2014). Slicing up global value chains. *Journal of Economic Perspectives*, 28(2):99–118.

Timmer, M. P., Inklaar, R., O'Mahony, M., and Van Ark, B. (2010). *Economic growth in Europe: A comparative industry perspective.* Cambridge University Press.

Timmer, M. P., Los, B., Stehrer, R., and Vries, G. J. D. (2016). An anatomy of the global trade slowdown based on the WIOD 2016 release. (November).

Traina, J. (2018). is Aggregate Market Power Increasing? Production Trends Using Financial Statements. Working Paper 17, Booth School of Business, University of Chicago.

Tørsløv, T. R., Wier, L. S., and Zucman, G. (2018). The missing profits of nations. Working Paper 24701, National Bureau of Economic Research.

Van Den Bergen, D., Bruil, A., Butler, B., van der Horst, A., Kranendonk, H., Mellens, M., Tanriseven, M., and Verbruggen, J. (2017). Herziening methode arbeidsinkomensquote. https://www.cpb.nl/sites/default/files/omnidownload/cbs-cpb-dnb-paper-herziening-methode-arbeidsinkomensquote.pdf.

van Heuvelen, G. H., Bettendorf, L., and Meijerink, G. (2018). Frontier firms and followers in the Netherlands: Estimating productivity and identifying the frontier. Background Document July, CPB, Den Haag.

van Heuvelen, G. H., Bettendorf, L., and Meijerink, G. (2019). Estimating Markups in the Netherlands. Background Document March, CPB, Den Haag.

Weir, G. (2018). Wage Growth Puzzles and Technology. RBA Research Discussion Papers rdp2018-10, Reserve Bank of Australia.

Wooldridge, J. M. (2009). On estimating firm-level production functions using proxy variables to control for unobservables. *Economics Letters*, 104(3):112–114.

World Bank (2015). *Purchasing Power Parities and the Real Size of World Economies. A Comprehensive Report of the 2011 International Comparison Program.* Washington, DC.

Chapter 5

Dutch Summary

In dit proefschrift verken ik de ontwikkelingen, en dynamiek van de inkomensaandelen gegenereerd door verschillende productiefactoren. Dit doe ik door naar verschillende niveaus te kijken: van het microniveau waar ik het arbeidsaandeel van individuele bedrijven bestudeer, tot productiviteitsvergelijkingen tussen hele landen.

Ondanks dat er een meerdere onderwerpen behandeld worden, is de rode draad die door het proefschrift loopt de rol die productiefactoren spelen bij productieprocessen en het genereren van inkomen. Het proefschrift bestaat uit drie losstaande hoofdstukken, die ieder een andere focus binnen dit bredere onderwerp behandelen. In hoofdstuk 2 (hoofdstuk 1 is de introductie) onderzoek ik de rol van superster bedrijven in de ontwikkelingen van de arbeidsinkomensquote (AIQ). Deze supersterren zijn bedrijven die zeer productief zijn, en grote marktaandelen binnen hun bedrijfstak bezitten. Omdat deze bedrijven vaak groot zijn, aandeel arbeidskosten in de totale omzet doorgaans laag. In het hoofdstuk constateer ik dat in een aantal bedrijfstakken de marktaandelen van de supersterren sterk is toegenomen. Door deze ontwikkeling is het totale arbeidsaandeel in inkomen afgenomen. Dit is de superster dynamiek.

In hoofdstuk 3 verken ik het inkomensaandeel dat niet toe te schrijven is aan de “standaard” productiefactoren; arbeid en materieel kapitaal. Dit inkomen is het inkomen dat toe te schrijven is aan immateriële productiefactoren. Het doel van dit hoofdstuk is om na te gaan in hoe dit inkomen verklaard kan worden met de bestaande databronnen van immaterieel kapitaal. De conclusie is dat deze data nog niet volledig toereikend is, en ik behandel in detail verschillende verklaringen voor dit resultaat. Verder vind ik een significante relatie tussen het inkomen van immateriële productiefactoren en indicatoren van globalisering d.m.v. handel.

In het laatste hoofdstuk verken ik productiviteitsverschillen tussen landen. De vernieuwing in dit hoofdstuk is dat natuurlijke kapitaalgoederen zoals ondergrondse voorraden van olie, maar ook goudmijnen worden meegenomen als kapitaalgoederen. Het incorporeren van deze productiefactoren is ingewikkeld omdat alleen bepaalde landen bedeeld zijn met bepaalde factoren, en anderen niet. Dit maakt vergelijkingen tussen landen met de standaard methodologie moeilijk. Om dit verhelpen maken we een aantal aanpassingen in de methodologie en laten we zien dat de rol van natuurlijk kapitaal met name belangrijk in productiviteitsvergelijking waarin landen zitten die sterk afhankelijk zijn van dit soort kapitaal. Bijvoorbeeld OPEC-landen, die vaak voor een groot gedeelte van hun BBP afhankelijk zijn van olie.